Comparison of different conflict resolution strategies in collaborative clustering

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Aim of this work: comparison of different conflict resolution strategies in collaborative clustering

Presentation of a new collaborative clustering approach using a genetic algorithm

Comparison of the methods on several data sets (artificial and UCI)
Introduction

Collaborative Clustering

Conflict Resolution Strategies

Genetic Approach

Experiments

Conclusion
Collaborative clustering

- There exists a lot of different clustering methods (and new ones are published everyday)

- Instead of creating a new one, we tried to make collaborate the existing ones

- We proposed a method of collaborative clustering which takes advantage of different clustering results

- The method consists in an automatic and mutual refinement of different clustering results

- The idea is to produce several different clustering results which collaborate to find an agreement about the clustering of a dataset
Data

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Tab.: The data.

Fig.: The data in a 2dim space.

Let $X = \{x_1, \ldots, x_n\}$ be the data to process.
**Clustering**

<table>
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<tr>
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<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

**Tab.:** The data.

▶ Let $C = \{ C_1, \ldots, C_K \}$ be one clustering result.

**Fig.:** Example of one clustering of the data.
Example of three different clustering results

(a) 3 clusters  
(b) 4 clusters  
(c) 7 clusters

Let $C = \{C^{(1)}, \ldots, C^{(N)}\}$ be the ensemble of clustering results.

Let $C^{(i)} = \{C_1^{(i)}, \ldots, C_{K(i)}^{(i)}\}$ be the $i^{th}$ clustering of the ensemble.
To compute the similarity between the different results, the intersections between each couple of clusters \((C^{(i)}_k, C^{(j)}_l)\), from two results \(C^{(i)}\) and \(C^{(j)}\), are computed in the **confusion matrix** \(\Omega^{(i,j)}\):

\[
\Omega^{(i,j)} = \begin{pmatrix}
\alpha_{1,1}^{(i,j)} & \ldots & \alpha_{1,K(j)}^{(i,j)} \\
\vdots & \ddots & \vdots \\
\alpha_{K(i),1}^{(i,j)} & \ldots & \alpha_{K(i),K(j)}^{(i,j)}
\end{pmatrix}
\]

where

\[
\alpha_{k,l}^{(i,j)} = \frac{|C_k^{(i)} \cap C_l^{(j)}|}{|C_k^{(i)}|} \tag{1}
\]
The confusion matrix

The table for \( \Omega^{(1,2)} \):

\[
\begin{array}{ccc}
C_1^{(2)} & C_2^{(2)} & C_3^{(2)} \\
C_1^{(1)} & 0.11 & 0.42 \\
C_2^{(1)} & 0.05 & 0.03 \\
C_3^{(1)} & 0.50 & \end{array}
\]

The table for \( \Omega^{(2,1)} \):

\[
\begin{array}{cccccc}
C_1^{(2)} & C_2^{(2)} & C_3^{(2)} & C_4^{(2)} & C_5^{(2)} & C_6^{(2)} & C_7^{(2)} \\
C_1^{(1)} & 0,13 & 0,43 & 1 & 0,55 & 0,98 & 0,02 \\
C_2^{(1)} & 0,87 & 0,57 & \end{array}
\]
The intercluster similarity

From these matrices ($\Omega^{(i,j)}$ and $\Omega^{(j,i)}$), a **similarity measure** is computed to compare two clusters of two different results.

This **intercluster similarity** is evaluated by observing their intersection of the clusters and by taking into account the distribution of the cluster $C_k^{(i)}$ in all the clusters of $C^{(j)}$ as follows:

$$S \left( C_k^{(i)}, C_l^{(j)} \right) = \rho_k^{(i,j)} \alpha_{l,k}^{(j,i)}$$  \hspace{1cm} (2)

where

$$\rho_k^{(i,j)} = \sum_{r=1}^{n_j} (\alpha_{k,r}^{(i,j)})^2$$  \hspace{1cm} (3)

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Collaborative clustering

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Then, this similarity measure is used to compute the corresponding cluster of each cluster, which is the most similar cluster in another result:

\[ \psi \left( C_k^{(i)}, C_l^{(j)} \right) = \arg \max_{C_l^{(j)} \in C^{(j)}} S \left( C_k^{(i)}, C_l^{(j)} \right) \]  \hspace{1cm} (4) 

This correspondence between the clusters of the different results is used to identify the conflicts between the different results.
The corresponding cluster

**Fig.:** $\psi \left( C_k^{(1)}, C^{(2)} \right)$

**Fig.:** $\psi \left( C_k^{(2)}, C^{(1)} \right)$
The detection of the conflicts consists in seeking in \( C \) all the couples \( (C^{(i)}_k, C^{(j)}) \), \( i \neq j \), such as \( S \left( C^{(i)}_k, \psi \left( C^{(i)}_k, C^{(j)} \right) \right) < 1 \), which means that the cluster \( C^{(i)}_k \) can not be exactly found in the result \( C^j \) :

\[
\text{conflicts}(C) = \left\{ (C^{(i)}_k, C^{(j)}) : i \neq j, S \left( C^{(i)}_k, \psi \left( C^{(i)}_k, C^{(j)} \right) \right) < 1 \right\} \tag{5}
\]

Each conflict \( K^{(i,j)}_k \) is identified by one cluster \( C^{(i)}_k \) and one result \( C^{(j)} \). Its importance, \( CI \left( K^{(i,j)}_k \right) \), is computed according to the intercluster similarity:

\[
CI \left( K^{(i,j)}_k \right) = 1 - S \left( C^{(i)}_k, \psi \left( C^{(i)}_k, C^{(j)} \right) \right) \tag{6}
\]
Example of a conflict

(a) 3 clusters
(b) 7 clusters

**Fig.**: Example of conflict between two results.
Example of a conflict

Fig.: Example of conflict between two results.
Example of a conflict

(a) 3 clusters
(b) 7 clusters

Fig.: Example of conflict between two results.

\[ CI \left( \mathcal{K}_{2}^{(1,2)} \right) = 0.573 \]
The conflict resolution

- The local resolution of a conflict $\mathcal{K}_k^{(i,j)}$ consists in applying an operator on each result involved in the conflict, $\mathcal{C}(i)$ and $\mathcal{C}(j)$, to try to improve their similarity.

- The operators which can be applied to a result are the following:
  
  - **merging** of clusters: some clusters are merged together,
  
  - **splitting** of a cluster into subclusters: a clustering is applied to the objects of a cluster to produce subclusters,
  
  - **reclustering** of a group of objects: one cluster is removed and its objects are reclassified in all the other existing clusters.

- The operator to apply is chosen according to the number of clusters involved in the conflict.
However, the application of the two operators (each one on a different result) is not always relevant.

To evaluate the similarity between two results, we defined a criterion $\gamma$, called local similarity criterion.

It is based on the intercluster similarity $S$ and a quality criterion $\delta$.

$$\gamma(i,j) = \frac{1}{2} \left( ps \cdot \left( \frac{1}{n_i} \sum_{k=1}^{n_i} \omega_k^{(i,j)} + \frac{1}{n_j} \sum_{k=1}^{n_j} \omega_k^{(j,i)} \right) + pq \cdot \left( \delta(i) + \delta(j) \right) \right)$$

(7)

where

$$\omega_k^{(i,j)} = S \left( C_k^{(i)}, \psi \left( C_k^{(i)}, C^{(j)} \right) \right)$$

(8)

and, $pq$ and $ps$ are given by the user ($pq + ps = 1$).
After the resolutions of the local conflicts, a **global application** of the modifications proposed by the refinement step is decided if their application improve the quality of the global result.

The **global agreement coefficient** $\Gamma$ is evaluated according to all the local similarities between each couple of results as follows:

$$\Gamma = \frac{1}{m} \sum_{i=1}^{m} \Gamma^i$$

where

$$\Gamma^i = \frac{1}{m - 1} \sum_{\substack{j=1, j \neq i}}^{m} \gamma^i,j$$
Workflow of the approach

\[ C : C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

Conflicts list

\[ \mathcal{K}^{(1)} \quad \mathcal{K}^{(2)} \quad \mathcal{K}^{(3)} \ldots \]
Workflow of the approach

$C : C^{(1)} C^{(2)} C^{(3)}$

Current solution

Conflicts list

$\mathcal{K}^{(1)} \mathcal{K}^{(2)} \mathcal{K}^{(3)} \ldots$

$C^{(1)}$
Workflow of the approach

\[ C : C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

Conflicts list

\[ K^{(1)} \quad K^{(2)} \quad K^{(3)} \ldots \]

Current solution

\[ C^{(1)} \quad C^{(3)} \]
Workflow of the approach
Workflow of the approach

Current solution

\[ C : \quad C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

Conflicts list

\[ \mathcal{K}^{(1)} \quad \mathcal{K}^{(2)} \quad \mathcal{K}^{(3)} \quad \ldots \]

\[ \rightarrow C^{(1)} \]

\[ \rightarrow C^{(3)} \]
Workflow of the approach

Current solution

\[ C : \]

\[ C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

Conflicts list

\[ K^{(1)} \quad K^{(2)} \quad K^{(3)} \ldots \]

Conflict resolution

\[ C^{(1)} \rightarrow C^{(1)'} \]

\[ C^{(3)} \rightarrow C^{(3)'} \]
Workflow of the approach

Current solution

\[ C : C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

Conflicts list

\[ \mathcal{K}^{(1)} \quad \mathcal{K}^{(2)} \quad \mathcal{K}^{(3)} \quad \ldots \]

Conflict resolution

\[ C^{(1)} \quad C^{(3)} \quad C^{(1)'} \quad C^{(3)'} \]

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Collaborative clustering
Workflow of the approach

Current solution

\[ C : \quad C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

Conflicts list

\[ K^{(1)} \quad K^{(2)} \quad K^{(3)} \quad \ldots \]

Conflict resolution

\[ C^{(1)} \rightarrow C^{(1)'} \]
\[ C^{(3)} \rightarrow C^{(3)'} \]
\[ C^{(1)'} \]
\[ C^{(3)'} \]
Workflow of the approach

\[ C : \]
\[
\begin{align*}
C^{(1)} & \\
C^{(2)} & \\
C^{(3)} & \\
\end{align*}
\]

Conflicts list

\[ K^{(1)} \]
\[
\begin{align*}
K^{(2)} & \\
K^{(3)} & \\
\cdots & \\
\end{align*}
\]

Conflict resolution

\[ C^{(1)} \rightarrow C^{(1)'} \]
\[
\begin{align*}
C^{(3)} & \\
\end{align*}
\]

\[ C^{(3)} \rightarrow C^{(3)'} \]
Workflow of the approach

Current solution

\[ C : \]
\[ C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

Conflicts list

\[ K^{(1)} \quad K^{(2)} \quad K^{(3)} \quad \ldots \]

Conflict resolution

\[ C^{(1)} \rightarrow C^{(1)'} \]
\[ C^{(3)} \rightarrow C^{(3)'} \]

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Collaborative clustering
Workflow of the approach

Current solution

\[ C : \quad C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

Conflicts list

\[ K^{(1)} \quad K^{(2)} \quad K^{(3)} \ldots \]

Conflict resolution

\[ C^{(1)} \rightarrow C^{(1)'} \]

\[ C^{(3)} \rightarrow C^{(3)'} \]

\[ C^{(1)} \quad C^{(3)} \quad C^{(1)'} \quad C^{(3)'} \]
Workflow of the approach

\[ C : \begin{align*}
    C^{(1)} & \quad C^{(2)} & \quad C^{(3)} \\
\end{align*} \]

Current solution

\[ K^{(1)} \quad K^{(2)} \quad K^{(3)} \ldots \]

Conflicts list

\[ C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

Conflict resolution

\[ C^{(1)} \rightarrow C^{(1)'} \]

\[ C^{(3)} \rightarrow C^{(3)'} \]

\[ C^{(1)} \quad C^{(3)} \quad C^{(1)'} \quad C^{(3)'} \]

New solution

\[ C' : \begin{align*}
    C^{(1)} & \quad C^{(2)} & \quad C^{(3)'} \\
\end{align*} \]
This first approach consists in choosing the worst conflict, i.e. the one having the highest conflict importance.

\[
\mathcal{K} := \arg \max_{\mathcal{K}(i) \in \tilde{\mathcal{K}}} CI (\mathcal{K}(i)) \quad (11)
\]

![WCC](image_url)
Stochastic conflict choice (SCC)

- This approach consists in choosing randomly a conflict to solve in the list of conflicts. This naive strategy assumes that solving a conflict with a high importance is not always relevant.

\[ \mathcal{K} := \text{random} \left( \tilde{\mathcal{K}} \right) \]  

\[ p(\mathcal{K}^{(i,j)}_k) = \frac{1}{N_c} = 0.10 \]  

Fig.: SCC
This approach is based on roulette-wheel selection or fitness proportionate selection well known in the field of evolutionary optimization. The conflict importance is used to associate a probability of selection with each conflict. In this case, the probability of each conflict is defined as

\[ p(K_{(i)}) = \frac{CI(K_{(i)})}{\sum_{j=1}^{N_c} CI(K_{(j)})} \]  

with \( N_c \) the number of conflicts.

\[ \mathcal{K} := K_{(i)} \mid \left( \sum_{j=0}^{i-1} p(K_{(j)}) \leq \nu \land \sum_{k=0}^{i+1} p(K_{(k)}) > \nu \right) \]  

(13)

\[ p(K_{(2,1)}^{(2,1)}) = \frac{CI(K_{(2,1)}^{(2,1)})}{\sum_{j=1}^{N_c} CI(K_{(j)})} = 0.17 \]
1. Introduction
2. Collaborative Clustering
3. Conflict Resolution Strategies
4. Genetic Approach
5. Experiments
6. Conclusion
The global agreement coefficient

- **Evolutionary algorithm** (EA) is a generic population-based metaheuristic optimization algorithm.

- An EA uses some mechanisms inspired by biological evolution: mutation, recombination, and selection.

- Candidate solutions to the optimization problem play the role of individuals in a population.

- A fitness function evaluates the quality of the solutions.

- An evolution of the population takes place after by repeated application of the operators (mutation, recombination, and selection).
In our framework, a **solution** will be a set of clustering results: $\mathcal{C}$

- The **fitness** function will be the global agreement value of the set: $\Gamma(\mathcal{C})$
- Instead of modifying iteratively one solution, we will have a **population** of solutions evolving together by **sharing information**

$\mathcal{C} : C^{(1)} \; C^{(2)} \; \cdots \; C^{(n)}$

**Fig.**: Representation of one solution.
The evolutionary steps

- **Initialisation of the population**: random application of operators (split, merge, reclustering) on the original solution
- **Selection**: tournament selection based on the global coefficient $\Gamma(C)$
- **Crossover**: creation of a new solution by mixing two existing ones
- **Mutation**: resolution of a randomly selected conflict

Fig.: The evolutionary process.
Workflow of the approach

\[ C : C^{(1)} \quad C^{(2)} \quad C^{(3)} \]
Workflow of the approach

Initial solution

\[ C : \quad C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

\[ C' : \quad C^{(1)}' \quad C^{(2)}' \quad C^{(3)}' \]
Workflow of the approach

Initial solution

\[ C : \quad \begin{array}{ccc}
C^{(1)} & C^{(2)} & C^{(3)}
\end{array} \]

\[ C' : \quad \begin{array}{ccc}
C^{(1)} & C^{(2)'} & C^{(3)'}
\end{array} \]

\[ C'' : \quad \begin{array}{ccc}
C^{(1)''} & C^{(2)} & C^{(3)''}
\end{array} \]
Workflow of the approach

Initial solution

\[ C : \begin{cases} C^{(1)} & C^{(2)} & C^{(3)} \\ \end{cases} \]

\[ C' : \begin{cases} C^{(1)} & (2)' & C^{(3)'} \end{cases} \]

\[ C'' : \begin{cases} C^{(1)''} & C^{(2)} & C^{(3)''} \end{cases} \]

...
Workflow of the approach

Initial population

\[ \mathbb{C} : \quad C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

\[ \mathbb{C'} : \quad C^{(1)} \quad C^{(2)'} \quad C^{(3)'} \]

\[ \mathbb{C''} : \quad C^{(1)''} \quad C^{(2)} \quad C^{(3)''} \]

...
Workflow of the approach

Initial population

C:

\[ C^{(1)} \quad C^{(2)} \quad C^{(3)} \]

C':

\[ C^{(1)} \quad C^{(2)'} \quad C^{(3)'} \]

C'':

\[ C^{(1)''} \quad C^{(2)} \quad C^{(3)''} \]

... 

The cross over operator

C:

\[ C^{(1)} \quad C^{(2)} \quad C^{(3)} \]
Workflow of the approach

**Initial population**

\[ C : \begin{bmatrix} C^{(1)} & C^{(2)} & C^{(3)} \end{bmatrix} \]

\[ C' : \begin{bmatrix} C^{(1)} & C^{(2)'} & C^{(3)'} \end{bmatrix} \]

\[ C'' : \begin{bmatrix} C^{(1)''} & C^{(2)} & C^{(3)''} \end{bmatrix} \]

... 

**The cross over operator**

\[ C : \begin{bmatrix} C^{(1)} & C^{(2)} & C^{(3)} \end{bmatrix} \]

\[ C' : \begin{bmatrix} C^{(1)'} & C^{(2)'} & C^{(3)'} \end{bmatrix} \]

...
Workflow of the approach

Initial population

C:

C(1)  C(2)  C(3)

C’:

C(1)  C(2)’  C(3)’

C’’:

C(1)’’  C(2)  C(3)’’

... 

The cross over operator

C:

C(1)  C(2)  C(3)

C’:

C(1)’  C(2)’  C(3)’

C’’:

C(1)’’  C(2)’’  C(3)’’

...
Workflow of the approach

**Initial population**

\[ \mathcal{C} : \mathcal{C}^{(1)} \mathcal{C}^{(2)} \mathcal{C}^{(3)} \]

\[ \mathcal{C}' : \mathcal{C}^{(1)} \mathcal{C}^{(2)'} \mathcal{C}^{(3)'} \]

\[ \mathcal{C}'' : \mathcal{C}^{(1)''} \mathcal{C}^{(2)} \mathcal{C}^{(3)''} \]

... 

**The cross over operator**

\[ \mathcal{C} : \mathcal{C}^{(1)} \mathcal{C}^{(2)} \mathcal{C}^{(3)} \]

\[ \mathcal{C}' : \mathcal{C}^{(1)'} \mathcal{C}^{(2)'} \mathcal{C}^{(3)'} \]

\[ \mathcal{C}'' : \mathcal{C}^{(1)''} \]

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Workflow of the approach

Initial population

\[ C: \begin{bmatrix} C^{(1)} & C^{(2)} & C^{(3)} \end{bmatrix} \]

\[ C': \begin{bmatrix} C^{(1)} & C^{(2)'} & C^{(3)'} \end{bmatrix} \]

\[ C'': \begin{bmatrix} C^{(1)''} & C^{(2)} & C^{(3)''} \end{bmatrix} \]

\[ \ldots \]

The cross over operator

\[ C: \begin{bmatrix} C^{(1)} & C^{(2)} & C^{(3)} \end{bmatrix} \]

\[ C': \begin{bmatrix} C^{(1)'} & C^{(2)'} & C^{(3)'} \end{bmatrix} \]

\[ C'': \begin{bmatrix} C^{(1)} & C^{(2)''} \end{bmatrix} \]
Workflow of the approach

Initial population

\[ C : [C^{(1)}, C^{(2)}, C^{(3)}] \]

\[ C' : [C^{(1)}', C^{(2)}', C^{(3)}'] \]

\[ C'' : [C^{(1)}'', C^{(2)}'', C^{(3)}''] \]

The cross over operator

\[ C : [C^{(1)}, C^{(2)}, C^{(3)}] \]

\[ C' : [C^{(1)}', C^{(2)}', C^{(3)}'] \]

\[ C'' : [C^{(1)}'', C^{(2)}'', C^{(3)}''] \]
Workflow of the approach

Initial population

\[ C : \begin{bmatrix} C^{(1)} & C^{(2)} & C^{(3)} \end{bmatrix} \]

\[ C' : \begin{bmatrix} C^{(1)} & (2)' & (3)' \end{bmatrix} \]

\[ C'' : \begin{bmatrix} (1)'' & C^{(2)} & (3)'' \end{bmatrix} \]

\[ \vdots \]

The cross over operator

\[ C : \begin{bmatrix} C^{(1)} & C^{(2)} & C^{(3)} \end{bmatrix} \]

\[ C' : \begin{bmatrix} C^{(1)'} & C^{(2)'} & C^{(3)'} \end{bmatrix} \]

\[ C'' : \begin{bmatrix} C^{(1)''} & C^{(2)'} & C^{(3)''} \end{bmatrix} \]

New solution

\[ C : \begin{bmatrix} C^{(1)} & C^{(2)} & C^{(3)} \end{bmatrix} \]

\[ C' : \begin{bmatrix} C^{(1)'} & C^{(2)'} & C^{(3)'} \end{bmatrix} \]

\[ C'' : \begin{bmatrix} C^{(1)''} & C^{(2)'} & C^{(3)''} \end{bmatrix} \]
Example of the evolution of the population

(a) Initial population

(b) Generation 50

(c) Generation 100
Comparison of the approaches

(d) Solutions of the iterative approach

(e) Solutions of the genetic approach
Experiments

- We **evaluated** the four proposed approaches on synthetic datasets included in the Cluster generators package \(^a\), and real-life datasets from the UCI repository.

- In all of the experiments, we used the **KMeans algorithm** as the base clustering method.

- Five instances of KMeans were randomly initialized with a number of clusters randomly picked in \([2; 10]\) to create the initial set of results.

- Then, the **different strategies of conflict resolution** were applied, each one individually, but starting from the same initial set of results (i.e. the same initial solution).

\(^a\)http://dbkgroup.org/handl/generators/
## Experiments

<table>
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<th>T</th>
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<th>Jaccard</th>
<th>Folks &amp; Mallows</th>
<th>F-Measure</th>
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<td>2d-4c-no0</td>
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<tr>
<td>- WCC</td>
<td>0.924</td>
<td>0.772 (±0.074)</td>
<td>0.872 (±0.045)</td>
<td>0.869 (±0.049)</td>
<td>0.824 (±0.066)</td>
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<tr>
<td>- RCC</td>
<td>0.872</td>
<td>0.745 (±0.095)</td>
<td>0.857 (±0.057)</td>
<td>0.850 (±0.065)</td>
<td>0.808 (±0.080)</td>
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<tr>
<td>- R-WCC</td>
<td>0.896</td>
<td>0.767 (±0.064)</td>
<td>0.871 (±0.037)</td>
<td>0.866 (±0.041)</td>
<td>0.831 (±0.045)</td>
</tr>
<tr>
<td>- GR</td>
<td>0.957</td>
<td>0.850 (±0.037)</td>
<td>0.919 (±0.021)</td>
<td>0.919 (±0.021)</td>
<td>0.890 (±0.028)</td>
</tr>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- WCC</td>
<td>0.897</td>
<td>0.643 (±0.163)</td>
<td>0.788 (±0.110)</td>
<td>0.769 (±0.137)</td>
<td>0.661 (±0.247)</td>
</tr>
<tr>
<td>- RCC</td>
<td>0.813</td>
<td>0.616 (±0.097)</td>
<td>0.768 (±0.066)</td>
<td>0.756 (±0.081)</td>
<td>0.693 (±0.074)</td>
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<tr>
<td>- R-WCC</td>
<td>0.800</td>
<td>0.612 (±0.110)</td>
<td>0.765 (±0.074)</td>
<td>0.750 (±0.088)</td>
<td>0.692 (±0.086)</td>
</tr>
<tr>
<td>- GR</td>
<td>0.941</td>
<td>0.769 (±0.056)</td>
<td>0.871 (±0.039)</td>
<td>0.868 (±0.038)</td>
<td>0.817 (±0.052)</td>
</tr>
<tr>
<td>10d-4c-no0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- WCC</td>
<td>0.852</td>
<td>0.900 (±0.100)</td>
<td>0.947 (±0.055)</td>
<td>0.944 (±0.060)</td>
<td>0.913 (±0.093)</td>
</tr>
<tr>
<td>- RCC</td>
<td>0.781</td>
<td>0.828 (±0.177)</td>
<td>0.898 (±0.111)</td>
<td>0.888 (±0.123)</td>
<td>0.856 (±0.148)</td>
</tr>
<tr>
<td>- R-WCC</td>
<td>0.875</td>
<td>0.937 (±0.080)</td>
<td>0.967 (±0.044)</td>
<td>0.965 (±0.048)</td>
<td>0.946 (±0.073)</td>
</tr>
<tr>
<td>- GR</td>
<td>0.887</td>
<td>0.958 (±0.011)</td>
<td>0.979 (±0.006)</td>
<td>0.979 (±0.006)</td>
<td>0.967 (±0.009)</td>
</tr>
<tr>
<td>10d-4c-no1</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- WCC</td>
<td>0.836</td>
<td>0.814 (±0.226)</td>
<td>0.890 (±0.144)</td>
<td>0.876 (±0.171)</td>
<td>0.806 (±0.296)</td>
</tr>
<tr>
<td>- RCC</td>
<td>0.835</td>
<td>0.925 (±0.104)</td>
<td>0.958 (±0.062)</td>
<td>0.956 (±0.066)</td>
<td>0.939 (±0.091)</td>
</tr>
<tr>
<td>- R-WCC</td>
<td>0.849</td>
<td>0.937 (±0.079)</td>
<td>0.967 (±0.043)</td>
<td>0.965 (±0.045)</td>
<td>0.954 (±0.058)</td>
</tr>
<tr>
<td>- GR</td>
<td>0.865</td>
<td>0.972 (±0.049)</td>
<td>0.985 (±0.026)</td>
<td>0.985 (±0.027)</td>
<td>0.979 (±0.037)</td>
</tr>
<tr>
<td>iris</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>- WCC</td>
<td>0.870</td>
<td>0.586 (±0.006)</td>
<td>0.763 (±0.006)</td>
<td>0.739 (±0.005)</td>
<td>0.615 (±0.010)</td>
</tr>
<tr>
<td>- RCC</td>
<td>0.811</td>
<td>0.589 (±0.043)</td>
<td>0.759 (±0.029)</td>
<td>0.740 (±0.035)</td>
<td>0.634 (±0.027)</td>
</tr>
<tr>
<td>- R-WCC</td>
<td>0.828</td>
<td>0.594 (±0.036)</td>
<td>0.762 (±0.024)</td>
<td>0.744 (±0.029)</td>
<td>0.636 (±0.027)</td>
</tr>
<tr>
<td>- GR</td>
<td>0.898</td>
<td>0.608 (±0.020)</td>
<td>0.771 (±0.009)</td>
<td>0.756 (±0.015)</td>
<td>0.638 (±0.018)</td>
</tr>
<tr>
<td>wine</td>
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</tr>
<tr>
<td>- WCC</td>
<td>0.740</td>
<td>0.712 (±0.099)</td>
<td>0.831 (±0.065)</td>
<td>0.826 (±0.074)</td>
<td>0.734 (±0.120)</td>
</tr>
<tr>
<td>- RCC</td>
<td>0.733</td>
<td>0.670 (±0.149)</td>
<td>0.800 (±0.100)</td>
<td>0.789 (±0.120)</td>
<td>0.658 (±0.249)</td>
</tr>
<tr>
<td>- R-WCC</td>
<td>0.743</td>
<td>0.747 (±0.064)</td>
<td>0.852 (±0.043)</td>
<td>0.850 (±0.045)</td>
<td>0.772 (±0.072)</td>
</tr>
<tr>
<td>- GR</td>
<td>0.803</td>
<td>0.752 (±0.139)</td>
<td>0.856 (±0.092)</td>
<td>0.849 (±0.115)</td>
<td>0.747 (±0.250)</td>
</tr>
<tr>
<td>segment</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>- WCC</td>
<td>0.829</td>
<td>0.328 (±0.024)</td>
<td>0.519 (±0.015)</td>
<td>0.491 (±0.028)</td>
<td>0.418 (±0.031)</td>
</tr>
<tr>
<td>- RCC</td>
<td>0.767</td>
<td>0.294 (±0.073)</td>
<td>0.510 (±0.062)</td>
<td>0.448 (±0.091)</td>
<td>0.363 (±0.140)</td>
</tr>
<tr>
<td>- R-WCC</td>
<td>0.787</td>
<td>0.301 (±0.064)</td>
<td>0.519 (±0.051)</td>
<td>0.457 (±0.076)</td>
<td>0.388 (±0.086)</td>
</tr>
<tr>
<td>- GR</td>
<td>0.849</td>
<td>0.332 (±0.078)</td>
<td>0.551 (±0.063)</td>
<td>0.493 (±0.091)</td>
<td>0.433 (±0.101)</td>
</tr>
</tbody>
</table>

**Tab.:** Evaluation of the different strategies on the artificial and UCI datasets.
Experiments

- The results indicate that the **genetic approach (GR)** always gives the best results on the different tested datasets.

- The **worst conflict choice strategy (WCC)** gives good results when the datasets are simple (i.e. 2d-4c-no0 and 2d-4c-no1 with four clusters with two attributes).

- When the datasets are more complex (with ten attributes and from UCI) the **roulette-wheel strategy (R-WCC)** gives better results than worst conflict choice strategy (WCC).

- The last strategy, **random selection (SCC)**, always gives the poorest results, except for one dataset (10d-4c-no1).

- These results are consistent as the **genetic resolution strategy (GR)** better explores the search space, and evaluates solutions which are not explored by the other iterative methods.
Summary:

- **Collaborative clustering** is a method which makes collaborate different clustering methods.
- A refinement step is used to modify the results.
- Different strategies of conflict order resolution have been presented and compared.
- We investigated the use of a genetic algorithm to optimize the collaboration.
- In future work, we plan to investigate new strategies of resolution.
Conclusion

- Thank you for your attention.
- Time for questions.

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