A Multi-Criteria Decision Method in the DBSCAN Algorithm for Better Clustering

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Abstract—This paper presents a solution based on the unsupervised classification for the multiple-criteria analysis problems of data, where the characteristics and the number of clusters are not predefined, and the objects of data sets are described by several criteria, and the latter can be contradictory, of different nature and varied weights. This work focuses on two different tracks of research, the unsupervised classification which is one of data mining techniques as well as the multi-criteria clustering which is part of the field of Multiple-criteria decision-making. Experimental results on different data sets are presented in order to show that clusters, formed using the improvement of the algorithm DBSCAN by incorporating a model of similarity, are intensive and accurate.

Keywords—Data mining; Clustering; Density-based clustering; Multiple-criteria decision-making

I. INTRODUCTION

Many studies showed that the resort to multiple-criteria analysis of the data in the classification establishes an effective approach for the extraction of the information, and that in optimal way in big databases described by several criteria, which are sometimes of different nature [1], [2]. To do it, several algorithms of different principles have been used in various different types of work. For example, UTADIS [3], [4][5] which presents the first and the only method belonging to the unique criterion synthesis approach. Basing on the utility functions apply only in the case cardinal data. In the first methods of assignment based on outranking relations approach, there is Trichotomic segmentation [6] and N-tomic (A Support System for Multicriteria Segmentation Problems) [7], had a limited number of categories and a fuzzy assignment. On the other side Electre-Tri [8] [9] [10] with its rather strong explanatory character, can handle any number of categories. There have been many developments since then [12]. But always with fuzzy assignment, an ordinal sorting and preorder structure. Thus the filtering method based on fuzzy preference introduced the fuzzy assignment approach and a binary relation of preference. The last techniques based on fuzzy indifference modeling, PROAFTN [13] [14], [15] and TRINOMFPC [16] are the methods of nominal sorting which require no particular structure.

However, it is noticed that all these methods have for basic principle supervised learning. This tendency is confirmed by the studies of D’Henriet [16], Zopounidis [2], Belacel [17] and others who list the various algorithms of multiple-criteria classification, and those classified in the family of multiple-criteria assignment based on supervised learning.

In spite of the superiority of the algorithms based on the supervised classification, their contribution remains limited in face to certain problems in which the information or/and the experience in the domain remain insufficient to redefine the clusters. To overcome this problem, some studies have begun researches by exploiting unsupervised learning.

In this sense, F.Anuska [1] introduces the research by evoking the multiple-criteria clustering problem and proposes the attempts of solution based on:

- The reduction of the multiple-criteria analysis problem in clustering to clustering problem with single criterion obtained as a combination of the criteria;
- The application of the techniques of clustering to grouping obtained by using single criteria clustering algorithms for each criteria;
- The application of constrained clustering algorithms where a chosen criterion is considered as the clustering criterion and all others are determining for the constraints;
- The modification of a hierarchical algorithm which would allow to solving the problem directly.

However, the indirect solutions proposed by F. Anuska direct towards NP-complete problems. And even direct solutions based on a hierarchical clustering method would be limited, because all the hierarchical clustering algorithms are efficient when the size of dataset does not exceed 100 objects [18], and they also are adapted for specific problems associated with areas having the separation or the regrouping of the objects, following the example of taxonomy in biology and in the natural evolution of the species [19].

Then Y. De Smet [21] and Rocha [20] used partition-based clustering algorithms as K-means. The first proceeded to the improvement of the K-means algorithm [22] by integrating a structural procedure preference (P, I, J) considering a triplet of binary relations, where p models strong preference, I Indifference relation and J incomparability relation. The second, more recent proposed the classification approach of a set of alternatives to a set of partially ordered categories by using the K-means method. Thereafter, these categories are classified
II. APPROACH PROPOSED: INVOLVING THE MULTI-CRITERIA CONCEPT IN THE DBSCAN ALGORITHM

Both data mining research and Multiple-criteria decision-making have specific and limited asset. As a result, the hybrid algorithm (DBSCAN modified) synergies the strengths of each algorithm in solving clustering problems.

A. DBSCAN (Density-Based Spatial Clustering of Applications with Noise)

DBSCAN [25], A Density Based Spatial Clustering of Application with Noise, is a density based clustering technique for discovering clusters of arbitrary shape as well as distinguishing noise. DBSCAN accepts a radius value $Eps (\varepsilon)$ based on a user defined distance measure and a value $MinPts$ for the number of minimal points that should occur within $Eps$ radius.

The following are some concepts and terms that explain the DBSCAN algorithm as presented in [25]:

- Eps-neighborhood: The Eps-neighborhood of a point $p$ " $N_{\varepsilon}(p)$ " is defined by:

$$N_{\varepsilon}(p) = \{ q \in D | p \neq q \land dist(p,q) \leq Eps \} ,$$

with $D$ as database of $n$ objects.

- Core object: A core object contains at least a minimum number $MinPts$ of other objects within its Eps-neighborhood.

- Directly density-reachable: A point $p$ is directly density-reachable from a point $q$ if $p \in N_{\varepsilon}(q)$ and $q$ is a core point.

- Density-reachable: A point $p$ is density-reachable from the point $q$ with respect to $Eps$ and $MinPts$ if there is a chain of points $p_1, ..., p_n$ with $p_1 = q$ and $p_n = q$ such that $p_{i+1}$ is directly density reachable from $p_i$ with respect to $Eps$ and $MinPts$, for $1 \leq i \leq n, p_i \in D$.

- Density-connected: A point $p$ is density connected to a point $q$ with respect to $Eps$ and $MinPts$ if there is a point $o \in D$ such that both $p$ and $q$ are density-reachable from $o$ with respect to $Eps$ and $MinPts$.

- Noise: A point in D is a noise object if it does not belong to any cluster.

- Cluster: A cluster C with respect to $Eps$ and $MinPts$ is a non-empty subset of D satisfying the following conditions:

$$\forall p, q : p \in C \land q \text{ density-reachable from } p \text{ with } Eps \text{ and } MinPts , \text{ then } q \in C \text{ (Maximality);}$$

$$\forall p, q : p \text{ density-connected to } q \text{ with } Eps \text{ and } MinPts \text{ (Connectivity).}$$

B. The model of similarity and dissimilarity

The model of comparison used in our algorithm is composed of four stages by calculating the following functions (e.g. first object: $alt1$ and second object: $alt2$) [30] [38]:

- The functions of similarity: $Similarity_{\text{alt1, alt2}} (1)$;

- The functions of the weighted similarity: $WeightedSimilarity (alt1, alt2)$ (2);

- The function of strong dissimilarity: $StrongDissimilarity (alt1, alt2)$ (3);

- The functions of the overall similarity: $OverallSimilarity (alt1, alt2)$ (4).

1) The function of similarity

In order to calculate the similarity (1) between two alternatives for each criterion “i” of the whole of criteria, we use the following functions:

$$Similarity_{i} (alt1, alt2) : D \times D \rightarrow \{-1,1\}$$

Such $D$ is the group of the objects (alternatives).
Similarity,\,(alt1,alt2) = \begin{cases} 
+1 \text{ if } |alt1_i - alt2_i| \leq \sigma_i \\
-1 \text{ if } |alt1_i - alt2_i| > \sigma_i 
\end{cases} \quad (1)

Each criterion is determined by a threshold $\sigma_i$, denotes marginal similarity of the criterion "i" with $0 \leq \sigma_i \leq MaxCr_i - MinCr_i$, where MaxCr_i and MinCr_i are respectively the maximal and the minimal value of the criterion "i".

According to the results of the first function, we can conclude that the similarity of two alternatives "alt1" and "alt2" come as follows:

- If $\text{Similarity,}_i(alt1,alt2) = +1$, then "alt1" and "alt2" are similar on criterion "i";
- If $\text{Similarity,}_i(alt1,alt2) = -1$, then "alt1" and "alt2" are not similar on criterion "i".

2) The function of the weighted similarity

In this stage, the importance of every criterion is introduced, the function of the weighted similarity (2) is the sum of product of similarity $\text{Similarity,}_i(alt1,alt2)$ (1) and the weight "pi" of every criterion "i".

$\text{WeightedSimilarity,}_i(alt1,alt2) : D \times D \rightarrow [-1,1]$;

$\text{WeightedSimilarity}(alt1,alt2) = \sum_i p_i * \text{Similarity,}_i(alt1,alt2) \quad (2)$

The results of this function can be classified in three cases:

- If $0 < \text{WeightedSimilarity}(alt1,alt2) \leq 1$, it implicates that it is more sure than not that "alt1" is similar to "alt2";
- If $-1 \leq \text{WeightedSimilarity}(alt1,alt2) < 0$, it implicates that it is more sure that "alt1" is not similar to "alt2" than the opposite case;
- If $\text{WeightedSimilarity}(alt1,alt2) = 0$, in this case we are in doubt whether object "alt1" is similar to object "alt2" or not.

To reinforce results and to limit doubt, by passing to the third stage, this latter can calculate strong dissimilarity between two alternatives.

3) The function of strong dissimilarities

This stage of the model allows to calculating strong dissimilarity (3) between two alternatives by using the following function:

$\text{StrongDissimilarity,}_i(alt1,alt2) : D \times D \rightarrow [0,1]$.

$\text{StrongDissimilarity,}_i(alt1,alt2) = \begin{cases} 
1 \text{ if } |alt1_i - alt2_i| \geq \delta^*_i \\
0 \text{ elseif} 
\end{cases} \quad (3)$

Where $\delta^*_i$ is the threshold of strong dissimilarity, such as:

$\delta_i < \delta^*_i \leq MaxCr_i - MinCr_i$.

If $\text{StrongDissimilarity,}_i(alt1,alt2) = 1$ implicates that "alt1" and "alt2" are strongly dissimilar on criterion "i".

In certain cases two alternatives can be similar in most criteria but there is a strong dissimilarity on the other criteria.

4) The functions of overall similarities

The last stage of the model of comparison allows us to introduce a total similarity (4). With the aid of following functions, we can finalize this model of comparison.

$\text{OverallSimilarity}(alt1,alt2) : D \times D \rightarrow [-1,1]$,

$\text{OverallSimilarity}(alt1,alt2) = mm(\text{WeightedSimilarity}(alt1,alt2),$

$\text{StrongDissimilarity,}_i(alt1,alt2),...,\text{StrongDissimilarity,}_i(alt1,alt2))$.

With this function: $mm : [-1,1]^q \rightarrow [-1,1]$

$mm(p_1,...,p_q) = \begin{cases} 
\max(p_1,...,p_q) \text{ if } p_i \geq 0 \\
\min(p_1,...,p_q) \text{ if } p_i \leq 0 \\
0 \text{ elseif} 
\end{cases} \quad (5)$

- If $\text{WeightedSimilarity}(alt1,alt2) > 0$ and there is no strong dissimilarity between both alternatives "alt1" and "alt2", it implicates that $\text{OverallSimilarity}(alt1,alt2) = \text{WeightedSimilarity}(alt1,alt2)$.

In that case we can conclude that both alternatives "alt1" and "alt2" are similar;

- If $\text{WeightedSimilarity}(alt1,alt2) > 0$ and there is a strong dissimilarity between both alternatives "alt1" and "alt2" with one or several criteria, it implicates that $\text{OverallSimilarity}(alt1,alt2) = 0$. In this case, we must prove the number of criteria where there is a strong dissimilarity and a weight of these criteria;

- If $\text{WeightedSimilarity}(alt1,alt2) \leq 0$ and there is a strong dissimilarity between both alternatives "alt1" and "alt2" on one or several criteria, it implicates that $\text{OverallSimilarity}(alt1,alt2) = -1$. Therefore both alternatives are dissimilar.
C. Description of the algorithm

$D$ denote a set of $n$ objects, where each object of this list is described on $m$ criteria of nominal, interval, ordinal and/or cardinal type. The evaluation of an object on criteria $j$ can be encoded in real interval bounded by the minimal and maximal value of this criteria "$i"$: $[\text{Max}_{Cr_j}, \text{Min}_{Cr_j}]$.

The relative importance of which criterion intervenes in assessing the comparison between two objects is not always equivalent and can influence the final result of a multi-criterion analysis. Therefore, the presence of a coefficient related to every criterion; witch reflects the importance in comparison with other criteria; is a primordial aspect in an algorithm to appoint a weight to every criterion with: $p_i \in [0,1]$ and $\sum_{i=1}^{n} p_i = 1$.

The algorithmic approach can be structured into the following steps:

1) Choose an arbitrary object " $a_{alt}$ " of the set of alternatives;

2) Calculate similarity (1) and strong dissimilarity (3) of this object " $a_{alt}$ " with every object of the set of alternatives;

3) Calculate the weighted similarity (2) of this object " $a_{alt}$ ";

4) Calculate the overall similarity (4) this object " $a_{alt}$ ";

5) Test the value of overall similar (4) and the presence of strong dissimilarity (3) which allows the determination if the alternative is considered to be a neighborhood of the object " $a_{alt}$ ";

6) Recover all objects density-connected to the object " $a_{alt}$ " on the parameters of overall similar (4) and the parameter "MinPts ":
   - If " $a_{alt}$ " is a core object, a cluster is formed;
   - If " $a_{alt}$ " is a point of border, therefore any points can be density-connected to " $a_{alt}$ " and the algorithm visits the following object of the set of alternatives;

7) This sequence continues until the density-connected cluster is completely and definitively found.

D. Multi-Criteria-DBSCAN Algorithm

```plaintext
Algorithm MC-DBSCAN(D, $\sigma$, $\delta^+$, $p$, MinPts)
//Inputs:
//D=[a_1, a_2, ..., a_n] set of alternatives(objects)
//$\sigma$ : threshold denote marginal similarity discrimination threshold of the criterion
//$\delta^+$ : is the threshold of strong dissimilarity
//MinPts : the number of minimal points that should occur within Eps radius
//Output:
//C={c1, c2, ..., ck} set of clusters
//Cluster_Label=0
for i=1 to |D|
    if $a_i$ is not cluster then
        for j=1 to |D|
            $L_1 = \text{Similarity}(a_i, a_j)$
            $L_2 = \text{StrongDissimilarity}(a_i, a_j)$
            $L_3 = \text{WeightedSimilarity}(L_1)$
            $X = X \cup \text{OverallSimilarity}(L_2, L_3)$
        end for
        if $|X| < \text{MinPts}$ then
            mark $a_i$ as noise
        else
            Cluster_Label= Cluster_Label+1
            add $a_i$ to cluster
        end if
    end if
    if $|X'| >= \text{MinPts}$ then
        end for
        add $a_i$ to cluster
    end if
end for

Algorithm 1: MC-DBSCAN Algorithm
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III. Experimentation and Results

To test and to assess the performances of our algorithm, we implemented the DBSCAN and the MC-DBSCAN algorithms by using Java as a language to implement the algorithms.

Performances of both algorithms DBSCAN and MC-DBSCAN are assessed on a few well-known datasets such as the Stulong [48], Iris [46], BasketBall [48], ColorHistogram [47], and some synthetic datasets of different shapes.
and other ones from UCI Machine Learning Repository [47] and KEEL Knowledge Extraction based on Evolutionary Learning [48].

For these tests to reflect correctly the performance of an algorithm, we compare the number of groups created by both algorithms and the percentage of non classified objects by varying parameters knowing that common parameters, ray locating maximum neighbors $\text{Eps} \in (\epsilon)$" and the minimum number of points that have to be present in Eps- neighborhood of this object "$\text{MinPts}$", we have the same values as both algorithms.

In the results table “Tab. 1” due to the global parameter Eps and MinPts, DBSCAN classifies objects in one class because it is not able to consider several criteria simultaneously.

The results presented in "Fig. 1" and "Fig. 2" prove that the classes obtained by the multi criteria clustering algorithm are very similar to groups that have been proposed by experts and that the percentage of non-classified objects is too low.

### TABLE I. COMPARISON OF RESULTS BETWEEN TWO ALGORITHMS: DBSCAN AND MC-DBSCAN

| Data        | Number of alternatives | Number of criteria | Parameters (Eps, $\text{MinPts}$) | DBSCAN | Non classified objects | MC-DBSCAN | Non classified objects |
|-------------|------------------------|--------------------|-----------------------------------|--------|------------------------|-----------|------------------------|
| Iris        | 150                    | 4                  | 0.2, 2.2 et 6                     | 2      | 4.5%                   | 3         | 0%                     |
|             |                        |                    | 0.4, 0.9 et 6                     | 1      | 0%                     | 7         | 15%                    |
|             |                        |                    | 0.6, 2.2 et 6                     | 1      | 0%                     | 3         | 4.5%                   |
|             |                        |                    | 0.9, 2.2 et 6                     | 1      | 0%                     | 2         | 3%                     |
| Stulong     | 1417                   | 5                  | 0.9, 80, 9                        | 1      | 1%                     | 7         | 0.28%                  |
|             |                        |                    | 0.6, 80, 9                        | 1      | 0.49%                  | 7         | 0.28%                  |
|             |                        |                    | 0.1, 80, 6                        | 1      | 8.04%                  | 7         | 0.28%                  |
| Color Histogram | 65535             | 32                 | 0.2, 0.9, 3                       | 1      | 0.012%                 | 8         | 0.012%                 |
|             |                        |                    | 0.01, 0.9, 4                      | 12     | 98.52%                 | 9         | 0.01%                  |
|             |                        |                    | 0.25, 0.9, 9                      | 2      | 0.19%                  | 9         | 0.016%                 |
|             |                        |                    | 0.6, 0.9, 5                       | 1      | 6.25%                  | 9         | 4.19%                  |
| BasketBall  | 96                     | 5                  | 0.6, 0.9, 6                       | 1      | 1%                     | 7         | 4.19%                  |
|             |                        |                    | 1.6, 9, 8                         | 1      | 0%                     | 7         | 5.20%                  |
|             |                        |                    | 0.4, 0.9, 4                       | 1      | 6.25%                  | 9         | 4.19%                  |

Fig. 1. Results assimilation of several clustering database by varying the parameters
The proposed algorithm allows for an experimental comparative study between the results by varying the relative importance regarding the criteria involved in the evaluation of assimilation between two actions. Regarding the proposed algorithm, the weight change may influence the final outcome of a multi-criteria analysis “Fig. 3”, while DBSCAN algorithm does not consider the indifference between the relative importances of each criterion.

The purpose of this final test is to evaluate the performance of the suggested algorithm on the same database by increasing
its size. In this test, we apply the MC-DBSCAN algorithm on
the database “Color Histogram” of a varying size between 1300
and 65000 objects by changing the input parameters.

Reading the “Fig.4” show that even if the size of the
database increases from 1300 up to 65,000 objects, the results
remain in the standard, which explains that the added objects
by increasing the size will affect the created classes but not the
creation of new classes.

IV. CONCLUSION

This work has eventually reached a new clustering
algorithm which contributes to resolving the multiple-criteria
clustering problem with various weights to the relative
importance to each criterion.

This new approach is based on the clustering by the
enhancement of the DBSCAN algorithm which was merged
with multiple-criteria decision-making.

However, it is necessary to highlight the need to further
improve the performance of the algorithm. Because MC-
DBSCAN like most clustering algorithms requires in advance a
manual determination of input parameters.

It becomes clear that is by minimizing the human
intervention relative to the determination of the input
parameters will give us a better result.

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