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Vertical Collaborative Clustering using Enriched Self-Organizing Maps

Ameni FILALI [#1], Chiraz JLASSI[#2], Najet AROUS[#3]

[#] *University of Tunis Manar, Laboratory LR-SITI ENIT*
ENIT, BP-37 Campus Univesitaire 1002 Tunis, Tunisia

[1] ameni.filali@gmail.com
[2] chiraz_jlassi@yahoo.fr
[3] najetarous@yahoo.fr

***Abstract*— Till now, knowledge-based clustering has effectuated on a unique dataset. In this study, we examine a situation that appears when there are different datasets. We are focused on a structure in revealing interests each of them, but, they need to be processed separately and independently. This leads to the principal concept of collaboration: The clustering approaches execute locally but cooperate by exchanging information about their results. We present two main development algorithms designed to vertical and horizontal collaboration.**

In this paper, we are interested in the vertical collaboration approach based on the enriched Self-Organizing Map (SOM_E) algorithm. This method consists in applying the SOM_E algorithm on different datasets where similar clusters can be found (same feature spaces and different observations), and besides to apply a collaborative approach on the obtained maps with the aim of transmitting knowledge between them. The proposed method has been tested on different datasets, and the experimental results have proved very hopeful performances.

***Keywords*—Collaborative clustering; unsupervised learning; vertical collaboration; Enriched Self-Organizing Maps (SOM_E).**

I. Introduction

In this paper, we are attenuated in the concept of collaboration at the level of information and the distinction between two principal models of collaboration, vertical and horizontal clustering [6].

We prove that this collaborative approach stands in keen contrast to the existing models of clustering and data analysis ([13], [12]). With the descriptive notation in place, we define a collection of detailed clustering methods.

Having a series of datasets existing at several organizations. These data could be representing customers of agencies, retail stores, and medical organizations. The data could contain records of various individuals. Also, they could also treat with the different individuals, but each dataset may have same descriptors (features).

The aim of each organization is to reveal important relationships in its dataset. Also, these organizations find that as there are other datasets, among their main strength is to learn about the reliance they're happening in order to detect the total information of the global structure. Hence, we do not have direct access to each datasets, which interdict us from collaborate the most important datasets into a unique dataset. Access can be refused due to confidentiality requirements. This process can also be tricky and difficult because it is probable to lose the identity of the dataset of the organization.

While estimating the value of supplemental external datasets, it is useful to control how the consensus that there could influence on the results from the data within the organization.

Collaborative clustering was first introduced by Pedrycz [6], using a fuzzy k-means algorithm. The principal concept of collaboration is: “the clustering methods perform locally but combine by exchanging information about their consensus” Pedrycz[6]. In addition, this vertical collaboration was introduced by N. Grozavu and Y. Bennani. ([8], [5]) inspired by the works of Pedrycz et al. [7] on the c-means collaborative learning.

In this work, we are introduced a vertical collaboration approach founded on the enriched SOM proposed by N.AROUS [2]. The aim of SOM is to find the referent vectors also to represent complex data, often noisy in a discrete space. In general, this is vector quantization patterns, which have special topological properties [1].

The SOM proposed by Kohonen [1] is a method that projects data from an input space to a lower dimensional output space. In SOM, the similar vectors in the input space are projected onto the map of neighboring neurons. During learning, competition between neurons with a single designation winner and neighborhood function between neurons. The winner of the selection rule, BMU (Best Matching Unit) is based on measuring Euclidean distance between the input vector and all the referent vectors of a map. The referent vector of the BMU is that which is nearest to the input vector, which represents the best.

The Studies ([1], [2]) have shown that the SOM is unable to decide the optimal way of membership of an input sample to a class in the classification process. Thus, they propose a method of enrichment of information in a Kohonen map.

During the learning phase, when an input sample is assigned to a winning neuron, the input vector, the label and its activation frequency are stored in the winning unit.

We integrate this information enrichment principle in SOM and we obtain the enriched SOM (SOM_E).

The remainder of this paper is planned as following: we show the principle of collaborative clustering in Section 2, after a short introduction of Self-Organizing Maps (SOM) algorithm.

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The vertical collaboration approach is presented in Section 3. The experimental results are illustrated in Section 4 before a conclusion with some future works for this approach.

II. COLLABORATION CLUSTERING

Collaborative clustering implies mechanisms of interaction. Note that collaboration can integrate a variety of descriptive schemes; two of them are the most fundamental. We focus to them as horizontal and vertical collaboration clustering. More detailed, given data sets X[1],X[2], . . .X[P] where P signify their number and X[ii] corresponds for the ii-th dataset.

While the collaboration clustering is shown in the next section, it is informative here to qualify the nature of the possible collaboration ([9], [11]).

In horizontal clustering, we treat with the same objects that are described in different feature spaces [7]. The graphic illustration of this model of clustering portrayed in figure 1 proves that each collaboration arises at the structural level through the information clusters constructed over the data; the clusters are presented as an auxiliary interface layer neighboring the data. The directed connections illustrate how the collaboration between different datasets occurs.

The width of the connections underlines the event that the intensity of collaboration can vary, according to the dataset associated and the purpose of the collaboration.

The collaborative clustering is founded on through the collaboration matrix. As we have the same patterns, this type of collaboration makes sense. The confidentiality of dataset has not been violated: we do not operate on individual models but on the finding information.

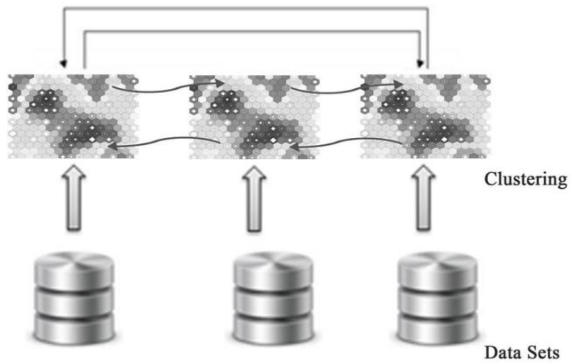


Fig.1. A general scheme of horizontal collaboration using SOM_E.

Vertical collaboration (figure2) is complementary to horizontal collaboration. In this case, the datasets are described in the same variables (feature space) but treat with different patterns. We consider that X[1],X[2], . . . ,X[P] are presented in the same variables, every of them consists of different models, dim(X[1]) = dim(X[2]) = . . . dim(X[P]), whereas X[ii] ≠ X[jj].We can illustrate the datasets as being empiled on every other.

In vertical collaboration, we are concerned with different objects but the same feature space. Besides, communication at the level of the referents becomes feasible. On account of the aggregate nature of the referents, the confidentiality requirement has been satisfied.

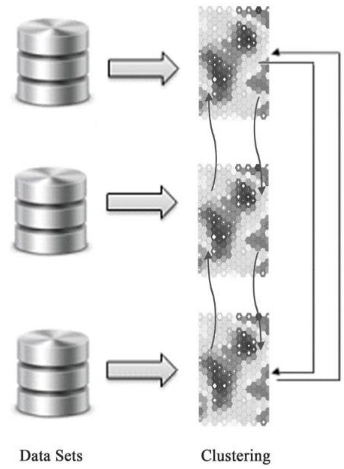


Fig.2. A general scheme of vertical collaboration using SOM_E.

Figure2 describes the general principle of vertical collaboration between several SOM_E maps. In this paper, we are interested particularly in the vertical collaboration.

III. VERTICAL COLLABORATION CLUSTERING

Here we introduce all necessary notations, and then we vocalize the optimization problem indirectly by objective function of collaborative clustering, and show the descriptive algorithm. The main concept of vertical collaboration is reaching when we are treating with different datasets where all objects are described in the same variables [10].

Note that, we cannot perform communication at the level of collaboration matrix because their dimensions would vary from set to set. The other alternative consists of referents of the datasets. They are presented in the same feature space, so in contrast to the horizontal collaboration, they could be a viable option.

The fundamental idea of vertical collaboration is: we want a neuron j of the ii-th SOM_E map and the same neuron j of the jj-th map, are very close in the sense of the Euclidean distance. Otherwise, neurons that represent to the various maps define groups of similar patterns. For this we have added a term to basic objective function of SOM_E maps to apply this constraint on the various boards in the collaborative phase. Formally, we have reached the following new proposed objective function:

$$R_V^{[ii]}(\chi,\mathrm{w}) = R_{SOM}^{[ii]}(\chi,\mathrm{w}) + R_{ColV}^{[ii]}(\chi,\mathrm{w}) \quad (1)$$

Where

$$R_{SOM}^{[ii]}(\chi,\mathrm{w}) = \sum_{i=1}^{N} \sum_{j=1}^{|w|} K^{[ii]}_{\sigma(j,\chi(x_i))} \left\| x_i^{[ii]} - w_j^{[ii]} \right\|^2 \quad (2)$$

$$R_{ColV}^{[ii]}(\chi,\mathrm{w}) = \sum_{jj=1,\, jj\neq ii}^{P} \alpha_{[ii]}^{[jj]} \sum_{i=1}^{N[ii]} \sum_{j=1}^{|w|} \left(K^{[ii]}_{\sigma(j,\chi(x_i))} - K^{[jj]}_{\sigma(j,\chi(x_i))}\right)^2 \left\| w_j^{[ii]} - w_j^{[jj]} \right\|^2 \quad (3)$$

Where P is the number of database, N [ii] is the number of individuals of the ii-th data set, |w| is the number of vectors of the prototypes map SOM_E ii which is the same for all maps, α[*ii*, *jj*] represents the collaboration coefficient justifying an effect of the jj-th dataset and affecting the system to be specified in the ii-th dataset. The interpretation of equation (3) is quite evident: the first expression is the basic objective function used to look for the structure of the ii-th dataset, and the second expression show the dissimilarities between the referents vector which have to be made smaller through the refinement of the collaboration matrix. This function is minimized for every dataset ii during the collaboration phase.

An important application of vertical collaboration introduces when treatment with enormous datasets.

Instead of clustering them in a unique pass, we separate them into single data sets, cluster each of them independently, and accord the results across the collaborative exchange of referents.

The vertical collaborative learning approach founded on enriched self-organizing maps is introduced in Algorithm 1 including two steps: the local step and collaboration step.

Algorithm1: Topological vertical collaborative learning

Random the collaboration matrix $\alpha^{[jj]}_{[ii]}$

1. Local step

For each BD[ii], ii = 1 à P

Find the prototypes minimizing the SOM_E :

$$W^{*} = \arg\min_{w} \left[R^{[ii]}_{SOM\_E}(\chi,\omega) \right]$$

2. Collaboration step

For the vertical collaboration of the[ii] map with [jj] map:

Update the referents of the [ii] map minimizing the objective function of the vertical collaboration applying the expression:

$$w^{*[ii]} = \arg\min_{w} \left[R^{[ii]}_{V}(\chi,\omega) \right] = \arg\min_{w} \left[R^{[ii]}_{SOM\_E}(\chi,\omega) + R^{[ii]}_{Col_V}(\chi,\omega) \right]$$

with:

$$W^{*[ii]}_{jk} = \frac{\sum_{i=1}^{N^{[ii]}} k^{[ii]}_{\sigma(j,\chi(x_i))} x^{[ii]}_{ik} + \sum_{jj=1, jj\neq ii}^{P} \sum_{i=1}^{N^{[ii]}} \alpha^{[jj]}_{[ii]} \left(k^{[ii]}_{\sigma(j,\chi(x_i))} - k^{[jj]}_{\sigma(j,\chi(x_i))} \right)^2 w^{[jj]}_{ik}}{\sum_{i=1}^{N} k^{[ii]}_{\sigma(j,\chi(x_i))} + \sum_{jj=1, jj\neq ii}^{P} \sum_{i=1}^{N} \alpha^{[jj]}_{[ii]} \left(k^{[ii]}_{\sigma(j,\chi(x_i))} - k^{[jj]}_{\sigma(j,\chi(x_i))} \right)^2}$$

IV. EXPERIMENTAL RESULTS

To evaluate the vertical collaboration method on SOM_E we tested this algorithm on different UCI datasets [5]. The proposed datasets are the following: Waveform, Wdbc, Pima, Madelon and Wine.

We will provide more details on the results generated on the waveform dataset to show the principle of this approach, particularly in the validation since the waveform dataset contains 21 pertinent variables and 19 noisy variables, thus it is helpful to present the effect of the collaboration in this approach.

A. Validation criteria

To validate this approach, we calculate the quantization error on several maps of various sizes and the purity index for each SOM_E. The quantization error is used to estimate the quality of an enriched self-organizing map. This error calculates the mean distance between each data vector and its BMU. It is measured in the following expression:

$$qe = \frac{1}{N} \sum \left\| x^{(i)} - w_{x_i} \right\|^2 \qquad (4)$$

Where N represents the number of datasets and $w_{x(i)}$ correspond to the closest referent to the vector xi. So, the values of the quantization error count on the size of datasets and on the sizes of generated maps, hence, these values can change depending on the dataset.

The purity index of a map calculates the mean purity of all the clusters of the map. Greater purity values signify better clustering. Having K clusters c_r, r = 1….K. First, we measure the purity of each cluster, which is determined by:

$$Purity = \sum_{r=1}^{K} \frac{|c_r|}{N} Pu(c_r) \qquad (5)$$

Where $|c^i_r|$ represents the number of patterns in c_r with class label i, $|c_k|$ corresponds to the number of datasets related to the cluster c_k, besides, $Pu(c_r)$ represents a fraction of the total cluster size that the largest class of objects attributed to that cluster illustrated. Hence, the total purity of the clustering solution is calculated a weighted sum of the individual cluster purities and determined as:

$$\mathrm{Pu}(c_r) = \frac{1}{|c_r|} \max_i (|c^i_r|) \qquad (6)$$

Where K represents the number of clusters and N show the number of patterns.

B. Datasets

All datasets are available on UCI Machine Learning Repository [5].

- Waveform: This data set consists of 5000 instances divided into 3 classes. This dataset contains 40 variables, 19 are all noise attributes. Each class is obtained from a combination of 2 of 3 "base" waves.
- Wdbc: Wisconsin Diagnostic Breast Cancer, This dataset includes 569 instances with 32 variables. Each dataset observation is labeled as benign (357) or malignant (212). Features are calculated from a digitized image of a fine needle aspirate (FNA) of a breast mass. They illustrate characteristics of the cell nuclei show in the image
- .Madelon: MADELON is an artificial dataset including data points divided in 32 clusters situated on the vertices of a five dimensional hypercube and arbitrarily labeled +1 or -1. The five dimensions establish 5 informative features. 15 linear cooperation of those features were added to form a series of 20 (redundant) informative features. Also, we used only 2600 observations from training set and from validation for which the classes were known.

- Wine: These data are the results of a chemical analysis of wines grown in the same region in Italy but derived from three different cultivars. The analysis determined the quantities of 13 constituents found in each of the three types of wines. The initial data set had around 30 variables, but for some reason I only have the 13 dimensional versions.
- Pima: Pima Indians Diabetes Database, Several constraints were placed on the selection of these instances from a larger database. ADAP is an adaptive learning routine that generates and executes digital analogs of perceptron-like devices. It is a unique algorithm. (Number of Instances: 768, Number of Attributes: 8 plus class)

C. Data partitioning

The datasets mentioned above are unified and grouped in subsets in order to have distributed dataset; we will use the vertical partitioning (figure3). In the case of vertical approach, we divide the datasets subsets so that each algorithm operates on the same features, however, with different set of individuals.

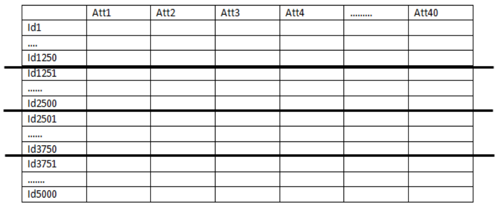


Fig.3. Vertical partitioning.

D. Experimental results on the waveform dataset

We are applied the vertical collaboration on waveform dataset in order to illustrate the amelioration of the collaborative clustering method because this dataset contains twenty noise features, and allows us to define a visualization of each result.

The obtained validation indices are shown in tables 1 and 2, and are discussed in this paper only those which changes importantly.

In order to get a datasets with the same features spaces and different patterns, the dataset waveform size 5000 × 40 was grouped into four subsets size 1250 × 40. We will use these four datasets to illustrate the different phases of vertical collaborative clustering using SOM_E. The collaboration matrix α has been set at [11, 11, 11, 11]. We fixed maps of dimension 10×10. During the local step, we use the unsupervised clustering SOM_E on the two first subset of data which is to train a SOM_E map for all the patterns of this dataset. Hence, we obtained as result two maps SOM_E1 and SOM_E2 which are illustrated in figure 4.

In this figure, X-axis and Y-axis represent respectively the variables and referents indices for these maps. Figure 4(a) shows the 100 referent vectors related with neurons of the first SOM_E1 map which has a purity index equal to 88.35% and a quantization error equal to 5.62.

Also, figure 4(b) shows the 100 referent vectors corresponding with neurons of the second SOM_E2 map which has a purity index equal to 87.77%, and a quantization error to 5.87. The generated results are summarized in table 1.

As is shown in the two above-mentioned figures, the referent vectors linked to these two maps are various owing to the fact that on the map in 4(a), each vector w_j is considered as the mean of individuals in the first dataset which has been associated on to the j-th neuron.

However, in figure 4(b), each vector w_j is considered as the mean of all the individuals of the second dataset which has been associated on to the j-th neuron.

Hence, we can't collaborate both datasets for reasons of confidentiality that prohibit the clustering of the all dataset on a unique SOM_E map.

Thereby, we will apply the contribution of phase cooperate the first dataset with the second card and similarly for the second map.

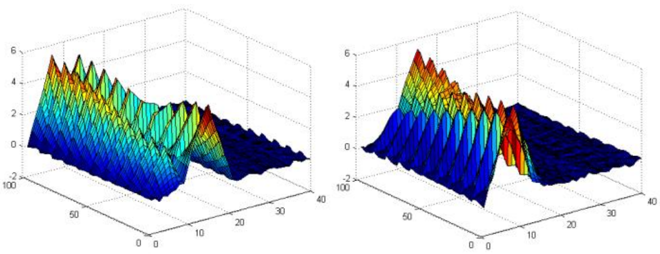
This would allow segmentation of patterns of the first dataset to a novel SOM_E map in order to obtain a like map to the one which we would have got if datasets had cooperated since we use the referent vectors of the first map connected with the second dataset and vice versa.

After the vertical collaboration step, the two maps must have similar referent vectors. Figure 5(c) and figure 5(d) show respectively the referent vectors generated on the first and second map after the vertical collaboration phase.

Figure 5(c) illustrates the 100 referent vectors SOM_E12 map obtained after the collaboration of the first dataset and the second SOM_E2 map of the local phase. Figure 5(d) illustrates the 100 referent vectors SOM_E21 map generated after collaboration of the second dataset and the first SOM_E1 map of the local phase.

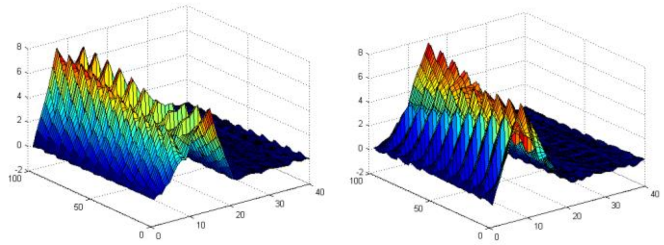
According to the two above-mentioned figures, it is evident that the referent vectors generated with these two maps are identical. This justifies that the collaboration really occurs and that two neurons j corresponding to the two collaborated maps show identical cells. The purities of these collaborated maps don't vary radically: SOM_E12 has a purity 88.12% and SOM_E21 87.96%. Likewise for the quantization errors: 5.64 for SOM_E12 and 5.70 for SOM_E21.

Also, we test a learning of the next two maps using the third and fourth datasets during the local phase of the vertical collaboration, and the figure 6(b) and 8(b) show these two maps. The SOM_E3 map generated from the third dataset has the pertinent features [1_21], and the most important variables (red color) were detected by the cells [15_50]. This map has the quantization error is equal to 5.19 and the accuracy is 91.62%.



(a) SOM_E1 (b) SOM_E2

Fig.4. Vertical collaboration: local phase (SOM_E).

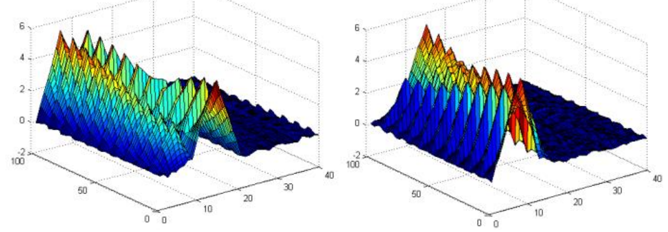


(c)SOM_E12 (d) SOM_E21

Fig.5. Vertical collaboration: collaboration phase for datasets 1 and 2.

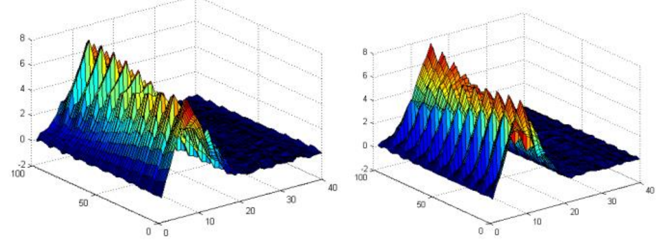
Contrariwise, the SOM_E4 map generated from the 4th dataset, the most significant variables ([10_22]) were taken by the cells [70_100] owing to the fact that of using different objects from the initial dataset. The purity index is 89.94% and quantization error equal to 5.49.

We apply the vertical collaboration between the first (SOM_E1) and third (SOM_E3). The SOM_E13 map was trained using the referent vector from the SOM_E3 map and as we can note in the figure 7(c) the most pertinent features ([1_22]) were detected by almost all the cells except some neurons [40_60] which illustrate that the collaboration between these two maps permitted to vary the information and to obtain more importance to the features [1_40] thanks to the SOM_E3 local map. Likewise for the SOM_E31 map which collaborate the third dataset with the SOM_E1 local map. Indeed, the variables [15_25] for the cells [60_100] are less significant compared to the SOM_E3 map due to the SOM_E1 map there the relating variables are less significant compared to the variables for the cells [1_ 40]. According to the table 1, the purities of these maps increase to 90.56% for the SOM_E31 map and to 89.80% for the SOM_E13 map that signify that due to the collaboration phase.



(a) SOM_E1 (b) SOM_E3

Fig.6. Vertical collaboration: local phase (SOM_E)

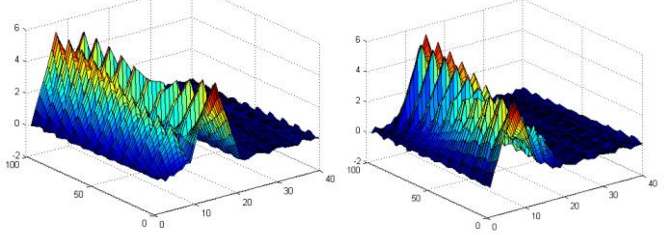


(c) SOM_E13 (d) SOM_E31

Fig.7.Vertical collaboration: collaboration phase for datasets 1 and 3.

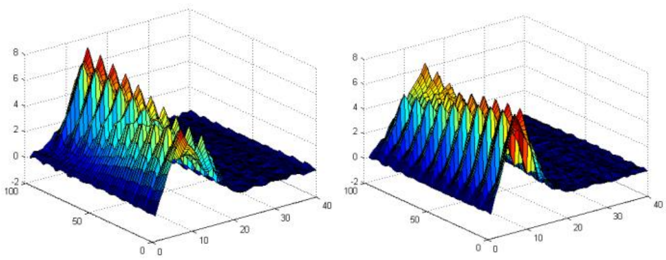
Like for the first and third local maps, the same analysis can be effectuate for the collaboration between the SOM_E1 map and SOM_E4 map. The results are described in the figure 9. The SOM_E14 map (figure9(c)) has the same structure as SOM_E1 (figure8(a)) by offering more significant to the variables [20_30] detected by cells [20_60] thanks to the collaboration with the SOM_E4 map.

On the contrary, the SOM_E41 map has a structure more identical to the SOM_E4 map and the variables [15_22] for the cells [80_100] decrease compared to the SOM_E4 map (figure 8(b)) due to the collaboration with the 1st map were these features are the less significant. The purity indices decrease to 89.26% for the SOM_E41 map and increase to 88.66% for the SOM_E14 map that signify that due to the collaboration phase. The results of the vertical collaboration experiment on the waveform dataset are analyzed in table 1. We remark that in most cases the purity index increases, as is the case for SOM_E21, SOM_E13 and SOM_E14 and the collaboration confidence parameters are identical seeing that all the maps are identical. Like all four datasets are described in the same feature space (variables). The purity index of the maps before and after the collaboration is greater compared to the horizontal collaboration. The quantization error is also justified for the maps generated after the collaboration with the maps having a lower quantization error.



(a)SOM_E1 (b) SOM_E4

Fig.8. Vertical collaboration: local phase (SOM_E)



(c) SOM_E14 (d) SOM_E41

Fig.9.Vertical collaboration: collaboration phase for datasets 1 and 4.

Table1: The vertical collaboration on the waveform dataset.

	SOM_E	
Measures	**Purity**	**Quantization error**
SOM_E1	88.35	5.62
SOM_E2	87.77	5.78
SOM_E3	91.62	5.19
SOM_E4	89.94	5.49
SOM_E12	88.12	5.64
SOM_E21	87.96	5.70
SOM_E13	89.80	5.22
SOM_E31	90.56	5.52
SOM_E14	88.66	5.57
SOM_E41	89.26	5.50

E. *Experimental results on others data sets*

We applied the same experimental process for other datasets and all computed indices are illustrated in table 2 for the vertical collaboration.

To validate the vertical collaborative approach on the other datasets, we will specify in this part the results measured after executing this approach. All maps have size 10x10. According to table 2, we remark that the purity index of SOM_E maps after vertical collaboration improves for all datasets and the quantization error decreases. This is thanks to the use of map's information connected with the collaborative dataset. Hence, we note that the collaboration confidence parameters are esteemed using the topological structure of the distant maps to detect the important collaboration links and to avoid a collaboration with are non-pertinent classification.

Concerning the Wdbc dataset, we remark that the purity index of the first SOM_E1 map after the collaboration with the second SOM_E2 map has increased. Contrarily, the purity of the second SOM_E2 map after the collaboration with the first SOM_E1 map has decreased. Also, the quantization error of the SOM_E21 map has increased.

For the database Madelon, we declare that the purity index after the collaboration and the quantization error are enhanced. Contrary, for the Pima dataset, we do not observe any improvement on the map SOM_E21 obtained after the collaboration SOM_E2 map with SOM_E1 map compared to those before.

For the Wine dataset, the quantization error has improved. During the collaboration approach, these results illustrate that the purity and the quantization error indices of each maps is not constantly enhanced and depends highly on the pertinence of the collaborative map and on the collaboration parameter.

In addition, we summarize that the vertical collaboration method enhances the resemblance between referent vectors. We illustrate as well that this vertical collaboration approach, often improves the quality of maps after the collaboration.

Table 2: The vertical collaborative approach on different datasets.

Datasets	**Map**	**Vertical Collaboration**	
		Purity	**QE**
WINE	**SOM_E1**	98.12	2.60
	SOM_E2	83.71	4.40
	SOM_E12	97.54	2.75
	SOM_E21	87.98	3.66
PIMA	**SOM_E1**	93.75	3.70
	SOM_E2	67.35	4.75
	SOM_E12	91.22	3.87
	SOM_E21	66.55	4.52
WDBC	**SOM_E1**	96.59	3.10
	SOM_E2	98.17	2.40
	SOM_E12	96.88	2.97
	SOM_E21	97.87	2.54
MADELON	**SOM_E1**	70.21	6.09
	SOM_E2	71.81	6.06
	SOM_E12	70.75	6.08
	SOM_E21	71.62	6.07

V. CONCLUSION

In this study, we have introduced an approach for clustering of different data obtained from various datasets using enriched self-organizing maps. The vertical collaboration is assigned to the problem of collaboration of several datasets.

Having the same feature space but describe different patterns as in the case of collaboration between several agencies.

Thanks to the principle of this approach, data confidentiality is conserved.

During the collaboration step, every dataset is cooperated with all the maps generated in the local step. Hence, each site apply its dataset and the information from other SOM_E maps, also training a novel map that is identical to the map that would be generated if we had centralized datasets and then clustering it. Therefore, the SOM_E maps obtained after the collaboration step are similar. This approach has been validated on several datasets and experimental results have illustrated very promising performance.

Different aims can be attained, which are: Combine the both approaches horizontal and vertical collaboration using SOM_E method: a new hybrid collaborative approach.

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