Discovering Complex Regularities: from Tree to Semi-Lattice Classifications

A. Faro, D. Giordano, and F. Maiorana

Abstract - Data mining uses a variety of techniques each of which is useful for some particular task. It is important to have a deep understanding of each technique and be able to perform sophisticated analysis. In this article we describe a tool built to simulate a variation of the Kohonen network to perform unsupervised clustering and support the entire data mining process up to results visualization. A graphical representation helps the user to find out a strategy to optimize classification by adding, moving or delete a neuron in order to change the number of classes. The tool is able to automatically suggest a strategy to optimize the number of classes optimization, but also support both tree classifications and semi-lattice organizations of the classes to give to the users the possibility of passing from one class to the ones with which it has some aspects in common. Examples of using tree and semi-lattice classifications are given to illustrate advantages and problems. The tool is applied to classify macroeconomic data that report the most developed countries' import and export. It is possible to classify the countries based on their economic behaviour and use the tool to characterize the commercial behaviour of a country in a selected class from the analysis of positive and negative features that contribute to classes formation. Possible interrelationships between the classes and their meaning are also discussed.

Keywords - Unsupervised classification, Kohonen networks, macroeconomics, Visual data mining, Cluster interpretation.

I. INTRODUCTION

DATA mining is a growing research field that deals with information extraction from a large amount of data. In this process we have argued elsewhere [1] that the use of "ad hoc" built tools can greatly improve techniques understanding and usage, and simplify tasks such as data understanding and preparation or results visualization. Clustering techniques are standard tools in data mining [3]. Kohonen neural networks, or Self-Organizing Maps (SOM) [2] are a preferred alternatives to traditional hierarchical clustering methods because of their better performances regarding noise tolerance, speed and robustness [4].

One key idea behind SOM is to transform a n-dimensional input data into a lower dimensional display (typically bi-dimensional) where the clusters are mapped, following the principle that elements that are close in the input space typically belong to neighboring classes.

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Maps consist of neurons that correspond to reference vectors whose dimensions is the same as the dimension of the input data. However, when dealing with n-dimensional data deciding the boundaries of the clusters first, and then cluster interpretation is often a challenge. Some approaches have been proposed to solve this problem, for example the method of the U-matrix used in conjunction with plane projections [4] to facilitate clusters interpretation; and a growing self-organized map that preserves hierarchical structures in the data is presented [5].

In this paper we use an alternative approach for clustering n-dimensional data based on a competitive, unsupervised learning algorithm enhanced with a tool to change and reshape the visualization space by adding, removing or deleting free neurons in the classification layer of the network.

The tool also provides automatic hints for optimal neural space reorganizations. Visualization facilities help the user to visualize the elements in each classes, and to point out for each class the main positive and negative features shared among its elements. It also provides explanations as to why each element belongs to a class in terms of the distance of this element from the centroid of the class, and the distance between the classes.

The paper will show that this information is important to decide if it is better to further divide a class into subclasses following a tree navigation scheme or to pass from the current class to a neighboring one in search of other relevant elements following a semi-lattice navigation scheme. The former approach is more suitable when one is interested in studying a system following the typical main features of their sub-systems (classes), whereas the latter approach is useful to study the interrelationships and the shared aspects, if any, between such sub-systems (classes).

The paper is organized as follows. Sect.2 illustrates the proposed approach contrasting it with the classical SOM. Sect.3 illustrates the tool's functionalities and the visual interface. Sect.3 presents a small example in order to clarify the two main types of classifications and related navigation schemes that are supported by the tool. Sect.4 reviews a previous work in economics data mining and summarizes the results from the application of the tool to a previously mined macroeconomics data set. Sect.5 offers some concluding remarks.

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II. Self Organizing Classification

Neural networks are often used to cluster input data. This grouping may be done automatically in an unsupervised way based on data correlations. The network architecture is composed by an input layer with as many nodes as the number of features of the items that must be classified and a competitive layer or output layer with as many nodes as the number of classes or clusters that must be found. Each input node is linked to all output nodes, and weights change during training until a termination criterion is satisfied.

Self-organizing Features Map (SOFM) is a competitive learning algorithm that has been widely used to obtain the mentioned unsupervised classification. At each iteration a winner (one neuron of the output layer) is found.

The winner is computed by finding the output neuron with the lowest distance between the input data and the weights. The weights of the winning neuron and the weights of neighboring neurons are updated by the following equation:

$$w(a_i) = w(a_i) + \nu\,\eta\,(m(i) - w(a_i))$$

where:

- **m** is the input matrix having N rows and M columns whose rows represents the input items and whose columns represent their features
- **m(i)** is the i-th row of matrix m representing the i-th input item,
- **w**(a_i) represent the weights linking the features of the input items to the output neurons belonging to a topological area a_i
- η is the learning rate of the network
- ν is a neighborhood function

As an example, assuming that the winning neuron for the current input is the neuron located at place (3,1) of the output bi-dimensional map, fig.1(A) shows the synaptic weights linking the input layer to the winning neuron that will be updated in the learning step.

A possible topological area involved in this learning step is also shown. Fig.1 (B) shows that if at the end of the learning phase, the winning neuron for the i-th item is the neuron located at place (1,4) then the item is considered to belong to first of the four classes drawn in the map.

The main problem of this algorithm is how to identify the classes, whereas the bi-dimensional map does not allow us to appreciate all the inter-classes relationships.

To avoid the mentioned limits, we adopt the slightly different neural network outlined in fig. 2 where the neurons involved in a learning step are the winning neurons and other neurons (usually two or three neurons) that are mostly activated by the current item.

The classes are given by the output neurons, i.e., if the neuron mostly activated by the i-th item is the j-th neuron, then the item belong to class j. Of course in our approach there is not topological similarity between output neurons since adjacent output neurons do not represent necessarily similar classes.
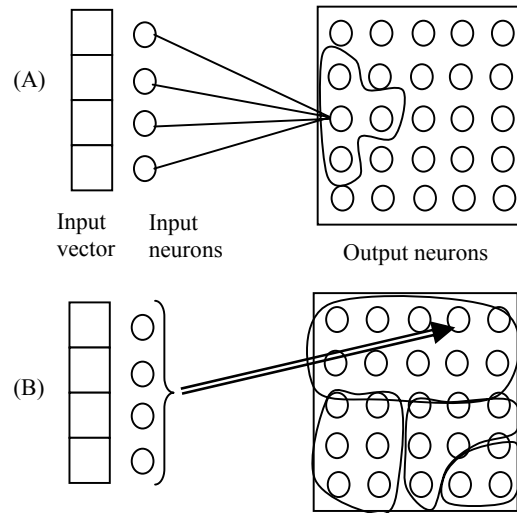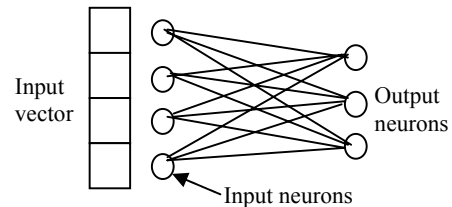

Figure 1 – Self-organizing Classification

Fig.2 – Unsupervised neural classifier

In particular in our approach we adopt learning formula:

$$w(b_i) = w(b_i) + \nu\,\eta\,(m(i) - w(b_i))$$

Such formula is similar to the SOFM one but with the difference that the output neurons constitute a layer rather than a map, and that the neurons involved in each learning steps do not belong to a topological area but are the set b_i of the most activated neurons.

Since the number of classes is not known a-priori, a suitable strategy has to be adopted in order to find the best class number C. This can be done by resorting to the notion of linking energy per class (L_C) whose formal definition is given below. The maximum number of classes is the one beyond which the linking energy per class E_C does not increase. Since under certain conditions E_C might increase indefinitely thus determining that the final classes consists of only one item, a suitable threshold T could be considered enough to avoid to transform the output layer by adding another output neuron to cluster the original set of items by one more class.

However, adding when $E_C < T$ an output neuron whose synaptic weights are randomly initialized, may cause a slow, possibly not effective, convergence towards a new cluster. Moreover, sometimes a better classification could be obtained by simply increasing the steps of the learning phase or by imposing, during the learning process, some small modification of the current synaptic values to avoid the

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algorithm remains trapped in some relative minimum. Finally a measure to evaluate if two classes are similar or not should be given. To manage automatically all these problems we define the following notion of linking energy:

$$E_c = 1 / L_c$$
$$L_c = \Sigma_j L_j / C \text{ for } j = 1 \text{ to } C$$

where L_j is the mean distance of the items of the class j from the point that mostly belongs to class j, i.e., the one having for any i ranging over Ij the following weights:

$$w_{ir} = 0 \text{ (if } r \neq j \text{) and } w_{ir} = 1 \text{ (if } r = j \text{).}$$

L_j is as follows:

$$L_j = (\Sigma_{i(Ij)} \ (\Sigma_{r,i\#j} \ w_{ir}^2 + (1-w_{ij})^2 \ ) \ )^{0.5} / N$$

where i(Ij) is the set of the items belonging to class j and w_{ir} (i.e., the synaptic weight connecting input i and the output neuron r at the end of the learning phase) measures how much the item of the class j belongs also to class r.

To find the distances between the classes r and s we calculate the quantities x_{hk} (h = 1 to C, j = k to C) as follows:

$$x_{hk} = \Sigma_{i(Ih)} \ w_{ik} / N_h$$

where N_h is the number of elements belonging to class h. The quantities x_{hk} represent for each class h the weights of the item P_h that is at the center of the items that belong to that class h. Thus the distance between any two classes r and s is simply the distance between P_r and P_h as follows:

$$D_{rs} = (\ \Sigma_j \ (x_{rj} - x_{sj})^2 \ )^{0.5}$$

These measures allows us to suggest an automated strategy to find the number of classes as follows:

1. if L_c has a high value or some D_{rs} shows a low value then increase the output neurons by one, and put the synaptic weights of this new neuron equal to the values of P_j, where j refers to the class with the highest L_j. If adding a new neuron does not produce an increase of E_c then delete the neuron with the highest L_j in the clustering obtained by C+1 output neurons and follow step 2.
2. if L_c or some D_{rs} have an intermediate value, then try to optimize the clustering first by moving the neuron of the highest L_j between the classes having lowest D_{rs} and then by increasing the number of the learning steps.

III. TOOL DESCRIPTION

The mining process supported by the tool consists of four phases: in the first phase we load the data from a text file and visualize them in a matrix **m**. We can choose the items to analyze (the rows of the matrix) and the features of each element (the columns). In the second phase, the data can be manipulated to improve data quality. In particular the original matrix is transformed into a similarity matrix as follows:

1. For each column j of the matrix m find the maximum Max_j and the minimum value Min_j and then normalize all the value of the column m(i, j) between 0 and 1, i.e.,

    $$m_{norm}(i, j) = (m(i, j) - Min_j))/ (Max_j - Min_j)$$

2. Compute the similarity matrix s(i,j) whose general element measures the similarity between item I and item J as the cartesian distance between rows i and j;

3. find the maximum Smax and the minimum value Smin of the matrix s and then normalize all the value s(i, j) between 0 and 1, i.e.,

    $$s(i, j) = (s(i, j) - Smin)) / (Smax - Smin)$$

Of course, if the original matrix represents how much an item is linked to the others, only the mentioned step 3 has to be performed. This shows that the tool is suitable not only to classify items expressed by features/keywords but especially items interrelated by links whose value (usually between 0 and 1) expresses how much an item is influenced or similar to the others. This is common in many domains (e.g., references in literature and scientific production, inspiration in art and design). In the third phase we use the self organizing network presented in the previous section to classify the data.

The tool interface (Fig. 3) allows the user to choose the items and which features to consider. The items are the rows whereas the features are the columns of the matrix m from which the proposed classification method starts. The similarity matrix s is then computed to be passed to the self organizing classification algorithm.

The neural network has to be initialized by setting some parameters such as the maximum number of cycles, the number of final classes, the updating neighborhood and the learning rate. The interface displays the current cycles and a progress bar indicates the status of the classification process.

The classification results are shown in another window (fig.4) where it is possible to know what items belong to each class and what are the features that have determined the insertion of the item in the class. The relevant features are identified by computing what are for each class the features that have a high or low value (positive and negative main features) for all the items of the class.

Moreover, for each item the tool shows the classes to which it belongs to in order of relevance. If this item is of some interest this is a simple way to find all the items that may be of relevance too, e.g., the items belonging to the classes that are of first and the second relevance for the item initially retrieved.

The last section of the tool deals with the restructuring strategy (fig.5), i.e., it gives an idea of how many items are belonging to the classes and indicates what is the best action to do for optimizing the clustering. This is obtained by a polar diagram where each line represents a class. The width of these lines represents the number of items. The color black and violet indicates that the class has no item or that it consists of

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only one item. If the length of the line is within internal circle then the class is dispersed and the insertion of a new neuron is suggested. The restructuring strategy may be implemented by the user following the indications of such diagram or the user may ask the tool to compute automatically and implement the best action to do.
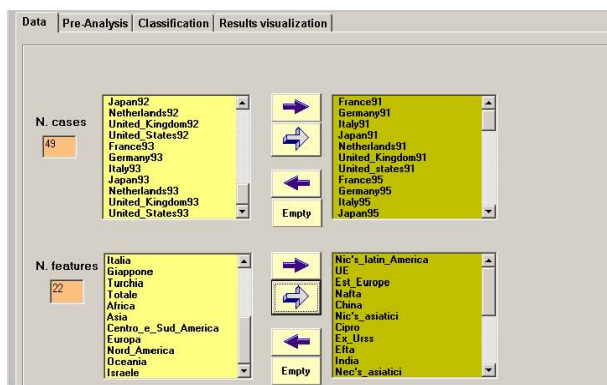

Fig.3 – Items/cases and features available for classification (on the left) and items/features chosen (on the right)
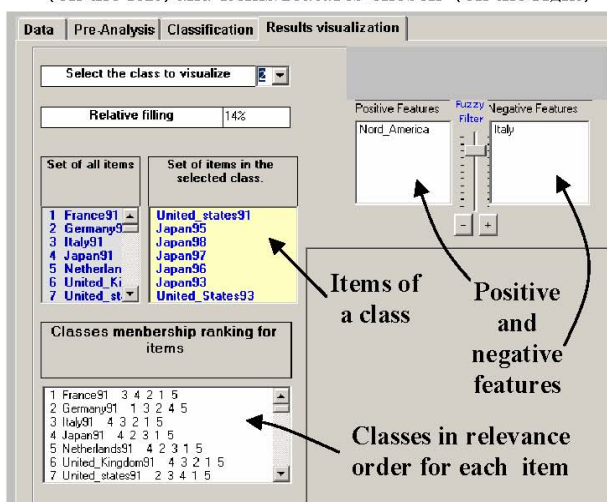

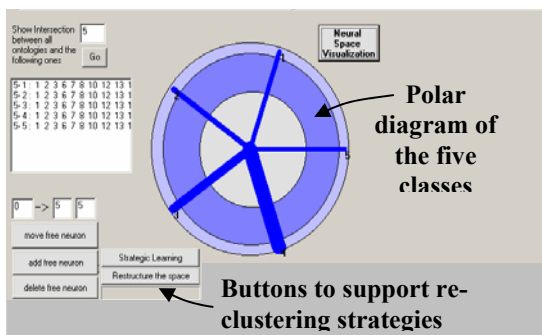Fig.4 - Classification results

Fig.5 - Polar diagram of the entire classification and strategic learning

IV. SEMI-LATTICE CLASSIFICATION : AN EXAMPLE

To illustrate the relevance of a semi-lattice classification, let us consider the following example inspired by the paper of Alexander [9] where the importance of such type of classification was for the first time clearly pointed out with particular reference to the field of system design. This example deals with five elements:

1. an apple that is a fruit with a circular form
2. a tennis ball that is a sport object with a circular form
3. a rugby ball that is a sport object with ellipsoidal form
4. a coconut that is a fruit with an ellipsoidal form
5. a pear that is a fruit with a circular form

Two tree classifications are possible as shown in fig.6A and fig.6B. The union of such classifications (fig.6C) constitutes a *Semi-Lattice Classification* (SLC) which is *by definition* a classification where at least one intersection C exists between two classes C_A and C_B (i.e., $C = C_A \cap C_B$) such that:

$$C \text{ is not empty}, C \neq C_A \text{ and } C \neq C_B$$

In fact in the classification of fig.6C, there are many intersections, e.g.,   C = {tennis-ball} = *sport* $\cap$ *circle*, that satisfy the above conditions. By using an SLC, we can reason on both the class features (e.g., the sectors *fruit* and *sport*) and on the aspects shared between classes (e.g., the *circular* and the *ellipsoidal forms*), thus avoiding excessive simplifications in the system analysis.
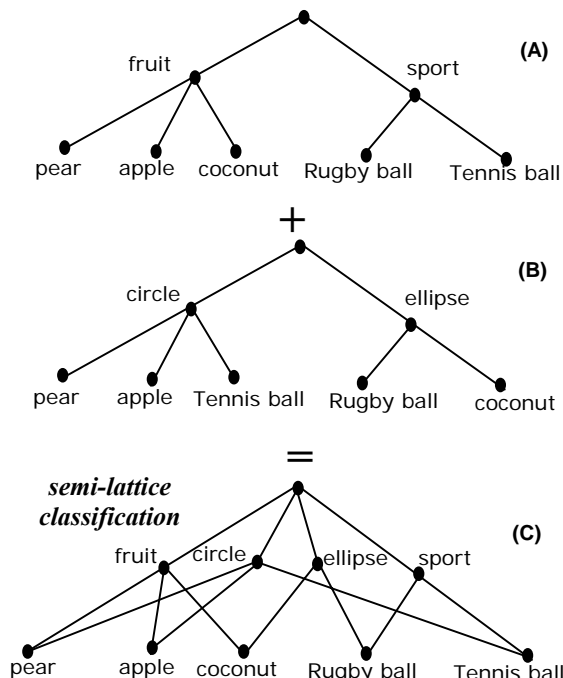

Fig.6 – Two tree classifications (fig.6A and 6B) developed following two different points of view are integrated into one SLC (fig.6C) that allows us to take into account both the above points of view.

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All the above classifications can be obtained by our tool according to the following procedure, called FR since it derives from the procedure Framing and Reframing introduced in [10] to reclassify design concepts for better supporting systems design. The FR procedure is as follows:

1. classify the data into the best number of classes Ci;
2. analyze the classification by observing for each class the elements and the main features (tree classification);
3. identify by using an interclass distance the pair of classes (Ci , Cj) whose distance is under a certain threshold, and that consequently may have something in common
4. take into account the set of all the elements belonging to both Ci and Cj;
5. delete (or decrease the weights of) the main features that characterize the classes Ci and Cj.
6. reclassify the class union of the classes Ci and Cj, i.e., Ci U Cj with respect to the features that have not been eliminated in the above step 5,
7. analyze such reclassification by observing for each class the elements and the common features;
8. analyze the overall system by simultaneously taking into account both the tree classification obtained in the step 2 and the re-classification obtained in step 6 pointing out the aspects shared between classes. This allows us to reason about data by using a *semi-lattice scheme*.

Fig.7 shows the Objects-Features matrix related to our example, where the value of the cell (i, j) is a measurement (comprised between 0 and 1) of how much the object indicated in the i-th row is characterized by the feature indicated in the j-th column.

	fruit	sport	circle	ellipse
pear	1	0	0.7	0.5
coconut	1	0	0	0.7
tennis-bal	0	1	1	0
rugby-ball	0	1	0	1
apple	1	0	1	0

Fig.7 - Objects-features matrix

By the application of the FR procedure we first obtain the classification shown in fig.8.
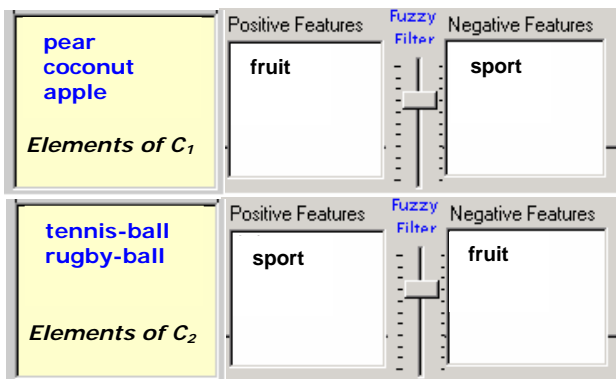

Fig.8 – Tree classification according to all the features

Since the distance between C_1 and C_2 is less than a given threshold, we reclassify the entire set of objects eliminating the main features *frui*t and *sport*, see fig.9A, that characterize the first classification. By using the proposed tool we obtain another classification, see fig.9B, that points out an alternative way of classifying the initial objects. If the user utilizes simultaneously the above two classifications, then she/he can reason on both the main features of the classes and the relevant aspects shared between the classes according to a semi-lattice reasoning scheme most suitable to understand complex systems.
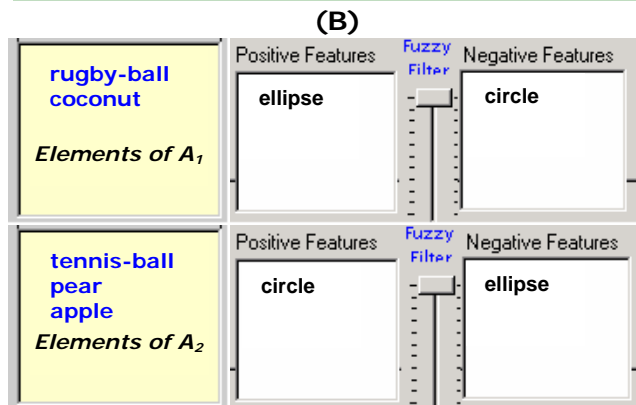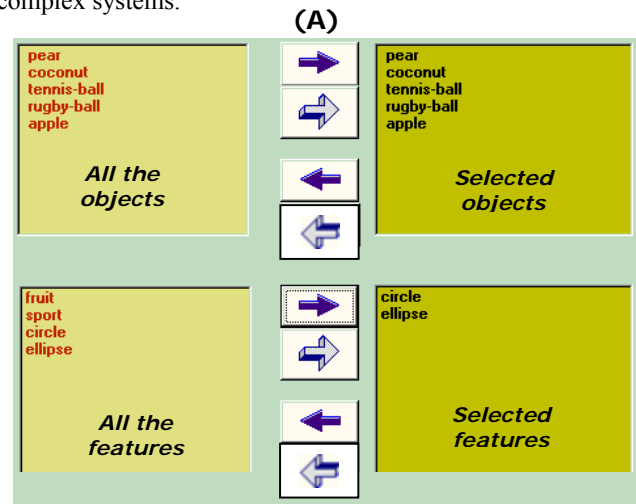

Fig.9 – In fig.9A a reclassification is activated according to procedure FR. Fig.9B shows the reclassification into the classes A_1 and A_2 according to relevant aspects shared between the initial classes.

V. APPLICATION TO MACROECONOMICS

Data mining usage in economics is a new developing field that uses data mining techniques not only to explore data but also to find a model for the data even if this model is often built without an underlying economic theory. This lack of economic theory in the data mining model often doesn't affect the quality of the results of the techniques used, especially regarding the predictive power of the models [6]. Financial information can be divided in economic and business information [7]. Business data deal with companies and their profit and expenses (microeconomics), economic data deal

with the national level (macroeconomics). A mining analysis of macroeconomics data was performed in Bordoni, Giordano and Spadaro [8] by mining a database with over 400,000 records regarding the import and export of the seven most economically developed countries in the period from 1990 to 1998. The analysis was carried out with IBM Intelligent Miner, by unsupervised neural clustering techniques. As a result, national product specialisation sectors were identified, the evolution of the economic structures of the considered countries was traced and the similarities among the countries were highlighted. In this paper we take into account the same set of data in order to evaluate the effectiveness of the proposed environment. The result of the classification showed that the best number of classes is five. This solution is a good compromise with classes containing a significant number of items with respect to the total number of items, and a distance between each element of the class and the class center not too great. The classes found contains the following items:

1. class one : Italy in the years 91, 92, 93, 95, 96, 97 and 98; Japan in the years 91 and 92; Netherlands in the years 91, 92, 93, 95, 96, 97 and 98; UK in the years 91, 92 and 93;
2. class two: Germany in the years 91, 92, 95, 96, 97, 98;
3. class three: France in the years 91, 92, 93, 95, 96, 97, 98; UK in the year 95, 96, 97, 98; Germany in 93;
4. class four: United States in the years 92, 95, 96, 97 98;
5. class five: United States in the years 91 and 93; Japan in the years 93, 95, 96, 97, 98.

This classification is in accordance with the one obtained by the Intelligent Miner, but the reasons underlying this clustering are more intelligible with our tool; in fact the tool indicates the market areas characterizing each class, allows us to easily select a subclass and go into further sub-clustering in order to better evaluate the competitors; it points out for each class the nearest classes and for each item the two or three classes to which it belongs for a detailed analysis of the market sectors of specific interest. Interestingly, by applying the FR procedure outlined in the previous section we note that:

- the macroeconomic system is highly specialized since more or less each country operates in a specific market area;
- the simultaneous presence of two countries in the same class (e.g., Italy and Netherlands) does not mean that they are in competition but only that they do not privilege any export area
- the only significant interrelationships is between classes 2 and 3. The reclassification of the countries belonging to the class union of such classes, i.e., $C_2 \cup C_3$, points out a small interference for a short time period among Germany, France and UK on the Europe market.

In this case the semi-lattice analysis is not particularly relevant, however, the situation could be different if one analyzes not the market as is, but how the market would be. In this latter case it is better to analyze the economic system from the point of view of the importing countries since such a classification could point out the countries that have the same socio-economic level but belong to two different classes, e.g., one depending on a principal export country, the other does not depend on any precise export country. This analysis, that takes into account the socio-economic level and the macroeconomic data, is very important to decide some new export strategy. In fact such semi-lattice analysis can point out new markets that emerge as the ones consisting of the countries that currently are not depending on any export country, but whose needs may become significant in a near future since they are similar to others that already use products of the selected business area.

V. CONCLUDING REMARKS

A method has been presented that has the advantage of being simple to use and affords the user interactive control over the classification process, which is important to gain an understanding of the data. Complex regularities may be pointed out by using the tool features, thus avoiding the simplification introduced by the bi-dimensional mapping of the SOFM classification or complicated SOFM based approaches that aim at enlarging the dimensions of the clustering space. To complement the method, a powerful visualization tool that allow the user to virtually navigate the N-dimensional classification space generated by the tool has been developed. By this tool it is very easy to understand if two classes may have some aspects in common and then if it is appropriate to activate a semi-lattice analysis. In fact this arises when in a Cartesian reference system, whose axes are the classes, more than one elements belong to the bisecting line between any two classes. Usability studies are being carried out to evaluate the advantages of a new 3D interface based on the above consideration for improving the discovery of complex regularities by highly interactive mining sessions.

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