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Classification of the students' intuitionistic fuzzy estimations by a 3-dimensional self organizing map

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Abstract: The aim of the present paper is to use the techniques of self-organizing map (SOM) in the process of e-learning to assess the students' knowledge on relevant topics in intuitionistic fuzzy form. The evaluation is formed on the basis of their answers. The self-organizing map is an effective tool for the visualization of high-dimensional data and its clustering. By clustering, students are classified into "similar" groups according to their intuitionistic fuzzy estimations. Thereby, a three-dimensional map for visualization of their knowledge in the intuitionistic fuzzy form is obtained.

Keywords: Intuitionistic fuzzy sets, Self-organizing map, Clustering.

AMS Classification: 03E72, 91C20.

1 Introduction

According to [7], self-organizing map (SOM) is an effective software tool for the visualization of high-dimensional data and it is used to turn data into useful task-oriented knowledge. It converts complex, nonlinear statistical relationships between high-dimensional data items into simple geometric relationships on a low-dimensional display. As it thereby compresses information while preserving the most important topological and metric relationships of the primary data items on the display, it may also be thought to produce some kind of abstractions. These two aspects, visualization and abstraction, can be utilized in a number of ways in complex tasks such as process analysis, machine perception, control, and communication.

In [11], a generalized net model (for generalized nets, GN, see [1, 2]) is designed, that presents how the process of SOM clustering evolves [5, 6]. In [14], a neural network is presented that determines the degree of assimilation, non-assimilation and uncertainty in students answers' evaluation based on a predefined set of criteria. The network could be used for the evaluation of the students' answers in the closed tests in e-learning. In [15], a multilayer perceptron is used for obtaining lecturers' evaluation using intuitionistic fuzzy estimations. It determines the degree of approval, disapproval and uncertainty in evaluating lecturers, based on the investigations of students answers to questionnaires. The evaluation is again based on a predefined set of criteria.

In the present paper, a SOM is used to data-mine the students' answers and facilitate their analysis by grouping the similar answers, i.e. clustering. Data mining is a process of discovering various models, patterns, and trends within a given collection of data [6]. Associations reflect relationships among items in databases, and have been widely studied in the fields of knowledge discovery and data mining. Most algorithms for mining association rules identify relationships among transactions using binary values. Transactions with quantitative values and items are, however, commonly seen in real-world applications.

2 Implementation

The SOM consists of a two-dimensional regular grid of nodes. All definitions related to the concept SOM are taken from [8, 9]. Clustering is the process of organizing objects into groups whose members are similar in some way [6]. A cluster is therefore a collection of objects which are "similar" and are "dissimilar" to the objects belonging to other clusters. A SOM is a type of artificial intelligence that is trained using unsupervised learning to produce a low-dimensional representation of the input space of the training samples, called a "map". The SOM is based on an issue of competitive learning. The net consists of a set A with n neurons, represented with weight vectors w_i. Furthermore, neurons are mutually interconnected and these bindings form some topological grid.

If we present a pattern x into this network, then exactly one neuron could be the winner and its weights are adapted proportionally to the pattern (the neuron is then closer). Neighbourhood $N(c)$ could be formally defined as a set of neurons that are topologically close to the winner. The winner of the competition is determined as the neuron with the minimum distance to the pattern. Then, adaptation of the weights proceeds. Weight vectors for the next iteration of the winner and neurons in the neighborhood are adapted so that current weights are modified (either added or subtracted) with a variance of current weight and input pattern. The weight vector of pattern is called "template vector" of that pattern. The SOM tries to adapt weights of neurons to cover the most dense regions and, therefore, SOM naturally finds data clusters [10, 11, 12] (Fig. 1).

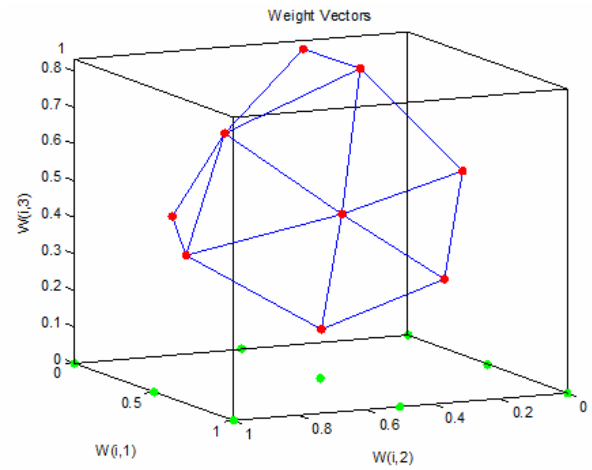

Figure 1. The weight centers of the clusters

The current SOM has 9 neurons in one layer. For the learning process the 27 different points are used that describe the working area of the neural network:

P = [0.0 0.0 0.0; 00. 0.0 0.5; 0.0 0.0 1.0; 0.0 0.5 0.0; 0.0 0.5 0.5; 0.0 0.5 1.0; 0.0 1.0 0.0;
0.0 1.0 0.5; 0.0 1.0 1.0; 0.5 0.0 0.0; 0.5 0.0 0.5; 0.5 0.0 1.0; 0.5 0.5 0.0; 0.5 0.5 0.5;
0.5 0.5 1.0; 0.5 1.0 0.0; 0.5 1.0 0.5; 0.5 1.0 1.0; 1.0 0.0 0.0; 1.0 0.0 0.5; 1.0 0.0 1.0;
1.0 0.5 0.0; 1.0 0.5 0.5; 1.0 0.5 1.0; 1.0 1.0 0.0; 1.0 1.0 0.5; 1.0 1.0 1.0]

The number of neurons determines the number of the clusters, in which corresponding points belong. In the two dimensional SOM, 3×3 neurons are used, i.e. 9 neurons.

As a test vector we use the students' estimations for the degree of the assimilation (μ) and the non-assimilation (ν) of obtained piece of information. These estimations are taken from [14]. They are represented by ordered pairs $\langle\mu, \nu\rangle$ of real numbers from the set $[0; 1]\times[0; 1]$. The degree of uncertainty $\pi = 1 - \mu - \nu$ represents those cases where the student is currently unable to answer the question being asked and needs additional information. Everywhere the ordered pairs have been defined in the sense of intuitionistic fuzzy sets [4].

The test vectors enter the inputs of the SOM. Every test vector hits the cluster that represents typical students' assimilation of the information. For example, in cluster number 9 we can see the students who exhibit the highest level of knowledge acquisition.

In Table 1 different test vectors are shown.

The results in the table can be explained, as follows:

- The test vectors with values $\mu \in [1.0, 0.8]$, $\nu \in [0.0, 0.2]$ and $\pi \in [0.0, 0.2]$ are classified in cluster 9. This reflects the cases when the students have a maximal assessments for the degrees of the assimilation of the obtained information (μ) and minimal assessments for the degree of the non-assimilation (ν) and for non-answered questions (π).
- The test vectors with values for $\mu \in [0.0, 0.15]$, $\nu \in [0.0, 0.1]$ and $\pi \in [0.8, 1.0]$ are classified in cluster 1. This reflects the cases when the students have a minimal assessments for the degrees of the assimilation (μ) and the non-assimilation (ν) of the obtained information and maximal assessments for non-answered questions (π).
- The test vectors with values $\mu \in [0.0, 0.1]$, $\nu \in [0.8, 1.0]$ and $\pi \in [0.0, 0.1]$ are classified in cluster 3. This reflects the cases when the students have a minimal assessments for the degrees of the assimilation (μ) and for non-answered questions (π) and maximal assessments for the degree non-assimilation (ν) of the obtained information.
- The test vectors with values $\mu \in [0.7, 0.75]$, $\nu \in [0.1, 0.2]$ and $\pi \in [0.1, 0.25]$ are classified in cluster 5. This reflects the cases when the students have a high (but not maximal) assessments for the degree of the assimilation of the obtained information (μ), low (but not minimal) assessments for the degrees of the non-assimilation (ν) and for non-answered questions (π).
- The test vectors with values $\mu \in [0.3, 0.55]$, $\nu \in [0.5, 0.7]$ and $\pi \in [0.0, 0.05]$ are classified in cluster 6. This reflects the cases when the students have a low (under or around the middle) for the degree of the assimilation of the obtained information (μ), middle (and above middle) assessments for the degree of the non-assimilation (ν) and low assessments for non-answered questions (π).

Number of test vector	Number of cluster
p1 = [0.0 0.9 0.1];	3
p5 = [0.1 0.1 0.8];	1
p10 = [0.9 0.0 0.1];	9
p15 = [0.15 0.35 0.5];	2
p20 = [0.75 0.0 0.25];	5
p25 = [0.1 0.8 0.1];	3
p30 = [0.15 0.1 0.75];	1
p35 = [0.3 0.7 0.0];	6
p40 = [0.8 0.1 0.1];	9
p45 = [0.5 0.45 0.05];	6
p50 = [0.05 0.05 0.9];	1
p55 = [0.05 0.90 0.05];	3
p60 = [0.5 0.5 0.0];	6
p65 = [0.0 0.05 0.95];	1
p70 = [0.9 0.1 0.0];	9
p75 = [0.05 0.0 0.95];	1
p80 = [0.0 0.5 0.5];	2
p85 = [0.65 0.35 0.0];	7
p90 = [0.0 1.0 0.0];	3
p95 = [0.0 0.0 1.0];	1
p100 = [1.0 0.0 0.0];	9
p105 = [0.0 0.9 0.1];	3
p110 = [0.5 0.5 0.0];	6
p115 = [0.1 0.9 0.0];	3
p120 = [0.8 0.0 0.2];	8
p125 = [0.55 0.0 0.45];	4
p130 = [0.7 0.2 0.1];	5
p135 = [0.45 0.5 0.05];	6
p140 = [0.0 1.0 0.0];	3
p145 = [0.0 0.0 1.0];	1
p150 = [0.05 0.95 0.0];	3
p155 = [0.9 0.1 0.0];	9
p160 = [0.55 0.45 0.0];	6
p165 = [0.8 0.2 0.0];	9
p170 = [0.5 0.0 0.5];	4
p175 = [0.7 0.1 0.2];	5
p180 = [0.8 0.0 0.2];	8
p185 = [0.1 0.45 0.55];	2
p190 = [0.7 0.3 0.0];	7
p195 = [0.05 0.05 0.9];	1
p200 = [0.0 1.0 0.0];	3

Table 1. Number of test vector and number of cluster

3 Conclusion

The SOM is an effective software tool for the visualization of high-dimensional data and as a tool for Data mining – process of discovering various models, summaries, and derived values from a given collection of data. It is used for the classification of the students' assessments of their assimilation and non-assimilation of the information in the learning process.

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