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An application of the InterCriteria Analysis and clusterization approach over a burnout dataset

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Abstract: In this investigation the level of burnout among the medical employees was analyzed. The InterCriteria Analysis (ICA) approach is used to find the dependences between different parameters characterizing the 139 medical employees from 6 medical centers. The aim is to analyze the correlations between the health indicators, by surveying with a developed questionnaire. The obtained data from the InterCriteria Analysis were clustered using an adaptive neural network.

Keywords: Burnout syndrome questionnaire, InterCriteria Analysis, Intuitionistic fuzzy sets, Self-organizing map.
2020 Mathematics Subject Classification: 03E72.

1 Introduction

In this study the prevalence of burnout among healthcare professionals was investigated. Burnout syndrome is a psychological syndrome that may emerge when employees are exposed to a very high and prolonged stress in the work environment with high job demands and low resources

[7, 12]. According to [12] burnout syndrome is defined by the three dimensions of exhaustion, cynicism, and inefficacy.

Dependencies between the various parameters describing the studied objects can be studied by applying InterCriteria Analysis (ICA) [2, 3]. This approach is based on intuitionistic fuzzy (IF) logic [1], where, in addition to the degrees of affiliation and non-affiliation, we also consider a degree of uncertainty. This makes its use appropriate in this type of research.

The purpose of the study of the data related to burnout is to analyze the correlations between the health parameters by surveying with a developed questionnaire. The obtained results of the intercriteria analysis are intuitionistic fuzzy pairs (IFPs) [4], which are in tabular form. The IFPs present the correlations between each pair of parameters. This necessitates their structuring. In the present study, we propose their clustering using an adaptive neural network [8, 9].

The self-educational self-organizing cards are a special kind of artificial neuron networks [8].

The purpose of self-organizing maps (SOM) is to transform the inlet model (signal) with a particular size in a two-dimensional diskette card and to transform it adaptively in a topologically orderly mode [11, 12].

In the SOM, the neurons are located in an N-shaped network is a separate case at $n = 2$.

This network is a one-layer straight stricture of neurons, located in lines and columns. The education on the neuron network is based on the principle of competitive training when one sole winner in the card (Figure 1).

Competition-type neural networks use the function of the winning neuron. In so-called competitive networks, the winning neuron has an output of 1, and all others have an output of 0.

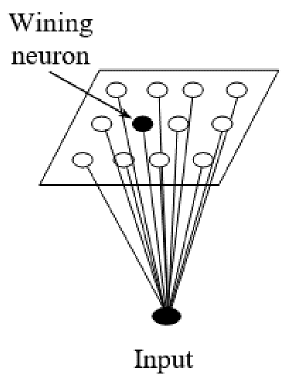

Figure 1. Winning neuron in neural network

The algorithm according to which SOM works (according to [10]) is the following:

Step 1. From a generator of occasional vectors $X_{cl} = (x_{c1}, x_{c2}, \ldots, x_{cn})^T$ a signal towards the input of the neuron network is given.

Step 2. The neuron network calculates the outputs the neurons on the basis of weight characteristics $W = (w_{j1}, w_{j2}, ..., w_{jm})^T\ j = 1, 2, 3, \ldots, l$ (at initial calculation occasional parameters for W are used).

Step 3. Defining the winning neuron (a standard function is used).

$$a_i = \text{compet}(n) = \begin{cases} 1, i = i^*, \text{ where } n_{i^*} \geq n_i, \text{and } i^* \leq i, \forall n_i = n_{i^*} \\ 0, i \neq i^* \end{cases}$$

Step 4. The calculate the surrounding area around winning neuron. Kohonen defines [10], the parameter h as 'topological surrounding'. For this purpose the parameter σ called 'effective width' of the topological surrounding is calculated,

$$\sigma(n) = \sigma_0 \exp(-\frac{n}{\tau_1}), \text{ for } n = 0, 1, 2, 3, ...,$$

where σ_0 is the initial effective width, n – the number of iterations of the algorithm and τ_1- a timely constant.

Step 5. Calculating the parameter for training $\eta_{j,i(x)}(n)$ according to

$$h_{j,i(x)}(n) = \exp\left(-\frac{d_{j,i}^2}{2\sigma^2(n)}\right), \text{ for } n = 0, 1, 2, 3, ...,$$

where the $d_{j,i}$ are defined as a "axial distance" between the winner i and the excited neuron j.

$$d^2{}_{j,i} = \left\| r_j - r_i \right\|^2,$$

In the case of a card where the discreet vector r_j defines the position of excited neuron j, and r_i defines the discreet position of the neuron winner.

Step 6. Calculating the parameter of training intensity $\eta(n)$ according to the formula

$$\eta(n) = \eta_0 \exp\left(-\frac{n}{\tau_2}\right) \text{ for } n = 0, 1, 2, 3, ...,$$

where is the initial characteristics η_0 of the parameter, and τ_2 is a timely constant.

Step 7. The new weight coefficients the two – dimensional neuron network alongside with the relation, created by Kohonen [8] are calculated.

$$w_j(n + 1) = w_j(n) + \eta_{j,i(x)}(n)h_{j,i(x)}(n)(x - w_j(n)),$$

where $X = (x_1, x_2, \ldots, x_n)^T$ are input vectors.

Step 8. For the effectiveness of the network about 2000 iterations have to be made. If $n < 2000$, go to Step l, otherwise move to Step 9.

Step 9. At the input of the trained neuron network the family of input vectors X is inserted. At the output of the one – dimensional network the classified values are obtained.

2 Materials and methods

In order to collect information about the burnout syndrome, a questionnaire with 64 questions was prepared. The questionnaire was divided into two parts. First part consists of 10 questions about gender, age, marital status, profession, work experience, type of medical facility, duty hours. The second part contains 54 questions that are connected with exhaustion, depersonalization and personal accomplishments of the of the respondents. Each question from the second part of the questionnaire is evaluated on a 5-point scale (1 – completely disagree, 2 – disagree, 3 – unsure, 4 – agree, 5 – completely agree).

With the prepared questionnaire, 139 medical employees from 6 medical centers were surveyed. The responders are distributed as follows:

- 38 are men (27.3%), 111 are women (72.7%);
- 66 are married (47.5%), 73 are single, divorced or widowed (52.5%);
- 17 are under the age of 30 (12.2%), 27 are in the age range of 30–40 (19.4%), 42 are in the 41–50 (30.2%), 38 are in the 51–60 (27.3%), and 15 are over 61 (10.8%);
- 27 are doctors with a specialty (19.4%), 35 are doctors without a specialty (25.2%), 52 are nurses (37.4%) and 25 are rehabilitators (18%);
- 77 have a surgical profile (55.4%), 62 have a therapeutic profile (44.6%);
- 21 have work experience from 1 to 5 years (15.1%), 11 from 6 to 10 years (7.9%), 18 from 11 to 15 years (12.9%), 6 from 16 to 20 years old (4.3%), 18 from 21 to 25 years old (12.9%), 24 from 26 to 30 years old (17.3%) and 41 have experience at 30 years old (29.5 %);
- 95 provide day and night shifts (68.3%);
- 108 work on Saturdays and Sundays (77.7%);
- 63 are available 24 hours a day (45.3%).

The above-mentioned parameters (C1 - C25) are arranged in rows of a table, and its columns list the medical facilities where the respondents work.

3 Implementation

The method of InterCriteria Analysis (ICA) is based on intuitionistic fuzzy sets, thus rendering account of the effects of uncertainty. Originally, ICA was being proposed in [2], and various aspects of its application over different data are given [6, 13]. The ICA method is applied over a table with 25 rows (for the parameters describing the profile of the respondents) and 6 columns (for medical facilities). As a result two tables for membership part and non-membership part of the intuitionistic fuzzy pairs [4] that represent an intuitionistic fuzzy evaluation of the relations between every pair of parameters (C1-C21) were obtained (table 1 and table 2). Following [3, 5] in order to categorize all the values of the resultant n (n – 1)/2 pairs of criteria, we need to define two thresholds, α and β, for the positive and for the negative consonance, respectively. The threshold values α and β are values on the [0; 1]-scale, changing with a precision step of 0.1. In our case the respective values, connected with the consonance/dissonance scale are as follows: strong positive consonance (0,95; 1), positive consonance (0,85; 0,95), weak positive consonance (0,75; 0,85). From the obtained 300 IFPs 7 IFPs are in a strong positive consonance, 33 IFPs are in a positive consonance and 20 IFPs is in a weak positive consonance.

Table 1. The membership parts of the Intuitionistic fuzzy pairs
of the different parameters describing the profile of the respondents

μ	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25
C1	1	0.5	0.9	0.9	0.5	0.5	0.3	0.8	0.6	0.9	0.9	0.5	0	0.8	0.8	0.6	0.4	0.5	0.5	0.4	0.9	0.4	0.9	0.6	0.9
C2	0.5	1	0.4	0.4	1	0.8	0.6	0.7	0.9	0.4	0.5	0.8	0.4	0.3	0.3	0.5	0.3	0.7	1	0.9	0.4	0.9	0.6	0.9	0.4
C3	0.9	0.4	1	1	0.4	0.4	0.2	0.7	0.5	0.8	0.8	0.4	0	0.9	0.9	0.6	0.3	0.6	0.4	0.3	1	0.3	0.8	0.5	0.8
C4	0.9	0.4	1	1	0.4	0.4	0.2	0.7	0.5	0.8	0.8	0.4	0	0.9	0.9	0.6	0.3	0.6	0.4	0.3	1	0.3	0.8	0.5	0.8
C5	0.5	1	0.4	0.4	1	0.8	0.6	0.7	0.9	0.4	0.5	0.8	0.4	0.3	0.3	0.5	0.3	0.7	1	0.9	0.4	0.9	0.6	0.9	0.4
C6	0.5	0.8	0.4	0.4	0.8	1	0.6	0.7	0.9	0.5	0.5	0.6	0.5	0.3	0.3	0.5	0.2	0.7	0.8	0.8	0.4	0.9	0.6	0.9	0.6
C7	0.3	0.6	0.2	0.2	0.6	0.6	1	0.5	0.5	0.3	0.3	0.8	0.4	0.1	0.1	0.2	0.5	0.3	0.6	0.6	0.2	0.7	0.4	0.5	0.4
C8	0.8	0.7	0.7	0.7	0.7	0.7	0.5	1	0.8	0.7	0.8	0.7	0.2	0.6	0.6	0.7	0.3	0.7	0.7	0.6	0.7	0.6	0.9	0.8	0.7
C9	0.6	0.9	0.5	0.5	0.9	0.9	0.5	0.8	1	0.5	0.6	0.7	0.4	0.4	0.4	0.6	0.2	0.8	0.9	0.8	0.5	0.8	0.7	1	0.5
C10	0.9	0.4	0.8	0.8	0.4	0.5	0.3	0.7	0.5	1	0.8	0.4	0	0.7	0.7	0.5	0.5	0.4	0.4	0.5	0.8	0.4	0.8	0.5	0.9
C11	0.9	0.5	0.8	0.8	0.5	0.5	0.3	0.8	0.6	0.8	1	0.5	0	0.7	0.7	0.6	0.3	0.5	0.5	0.4	0.8	0.4	0.9	0.6	0.8
C12	0.5	0.8	0.4	0.4	0.8	0.6	0.8	0.7	0.7	0.4	0.5	1	0.3	0.3	0.3	0.4	0.4	0.5	0.8	0.7	0.4	0.7	0.6	0.7	0.4
C13	0	0.4	0	0	0.4	0.5	0.4	0.2	0.4	0	0	0.3	1	0	0.1	0.2	0.1	0.3	0.4	0.4	0	0.5	0.1	0.4	0.1
C14	0.8	0.3	0.9	0.9	0.3	0.3	0.1	0.6	0.4	0.7	0.7	0.3	0	1	0.9	0.5	0.2	0.5	0.3	0.2	0.9	0.2	0.7	0.4	0.7
C15	0.8	0.3	0.9	0.9	0.3	0.3	0.1	0.6	0.4	0.7	0.7	0.3	0.1	0.9	1	0.5	0.2	0.5	0.3	0.2	0.9	0.2	0.7	0.4	0.7
C16	0.6	0.5	0.6	0.6	0.5	0.5	0.2	0.7	0.6	0.5	0.6	0.4	0.2	0.5	0.5	1	0.2	0.6	0.5	0.4	0.6	0.4	0.7	0.6	0.5
C17	0.4	0.3	0.3	0.3	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.4	0.1	0.2	0.2	0.2	1	0.2	0.3	0.4	0.3	0.3	0.3	0.2	0.4
C18	0.5	0.7	0.6	0.6	0.7	0.7	0.3	0.7	0.8	0.4	0.5	0.5	0.3	0.5	0.5	0.6	0.2	1	0.7	0.6	0.6	0.6	0.6	0.8	0.4
C19	0.5	1	0.4	0.4	1	0.8	0.6	0.7	0.9	0.4	0.5	0.8	0.4	0.3	0.3	0.5	0.3	0.7	1	0.9	0.4	0.9	0.6	0.9	0.4
C20	0.4	0.9	0.3	0.3	0.9	0.8	0.6	0.6	0.8	0.5	0.4	0.7	0.4	0.2	0.2	0.4	0.4	0.6	0.9	1	0.3	0.9	0.5	0.8	0.4
C21	0.9	0.4	1	1	0.4	0.4	0.2	0.7	0.5	0.8	0.8	0.4	0	0.9	0.9	0.6	0.3	0.6	0.4	0.3	1	0.3	0.8	0.5	0.8
C22	0.4	0.9	0.3	0.3	0.9	0.9	0.7	0.6	0.8	0.4	0.4	0.7	0.5	0.2	0.2	0.4	0.3	0.6	0.9	0.9	0.3	1	0.5	0.8	0.5
C23	0.9	0.6	0.8	0.8	0.6	0.6	0.4	0.9	0.7	0.8	0.9	0.6	0.1	0.7	0.7	0.7	0.3	0.6	0.6	0.5	0.8	0.5	1	0.7	0.8
C24	0.6	0.9	0.5	0.5	0.9	0.9	0.5	0.8	1	0.5	0.6	0.7	0.4	0.4	0.4	0.6	0.2	0.8	0.9	0.8	0.5	0.8	0.7	1	0.5
C25	0.9	0.4	0.8	0.8	0.4	0.6	0.4	0.7	0.5	0.9	0.8	0.4	0.1	0.7	0.7	0.5	0.4	0.4	0.4	0.4	0.8	0.5	0.8	0.5	1

Table 2. The non-membership parts of the Intuitionistic fuzzy pairs
of the different parameters describing the profile of the respondents

v	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25
C1	0	0.5	0.1	0.1	0.5	0.4	0.6	0.2	0.4	0.1	0	0.5	0.4	0.2	0.1	0.1	0.3	0.4	0.5	0.6	0.1	0.5	0.1	0.4	0
C2	0.5	0	0.6	0.6	0	0.1	0.3	0.3	0.1	0.6	0.4	0.2	0	0.7	0.6	0.2	0.4	0.2	0	0.1	0.6	0	0.4	0.1	0.5
C3	0.1	0.6	0	0	0.6	0.5	0.7	0.3	0.5	0.2	0.1	0.6	0.4	0.1	0	0.1	0.4	0.3	0.6	0.7	0	0.6	0.2	0.5	0.1
C4	0.1	0.6	0	0	0.6	0.5	0.7	0.3	0.5	0.2	0.1	0.6	0.4	0.1	0	0.1	0.4	0.3	0.6	0.7	0	0.6	0.2	0.5	0.1
C5	0.5	0	0.6	0.6	0	0.1	0.3	0.3	0.1	0.6	0.4	0.2	0	0.7	0.6	0.2	0.4	0.2	0	0.1	0.6	0	0.4	0.1	0.5
C6	0.4	0.1	0.5	0.5	0.1	0	0.4	0.2	0	0.4	0.3	0.3	0	0.6	0.5	0.1	0.4	0.1	0.1	0.1	0.5	0.1	0.3	0	0.4
C7	0.6	0.3	0.7	0.7	0.3	0.4	0	0.4	0.4	0.6	0.5	0.1	0.1	0.8	0.7	0.4	0.1	0.5	0.3	0.3	0.7	0.3	0.5	0.4	0.6
C8	0.2	0.3	0.3	0.3	0.3	0.2	0.4	0	0.2	0.3	0.1	0.3	0.2	0.4	0.3	0	0.4	0.2	0.3	0.4	0.3	0.3	0.1	0.2	0.2
C9	0.4	0.1	0.5	0.5	0.1	0	0.4	0.2	0	0.5	0.3	0.3	0	0.6	0.5	0.1	0.5	0.1	0.1	0.2	0.5	0.1	0.3	0	0.4
C10	0.1	0.6	0.2	0.2	0.6	0.4	0.6	0.3	0.5	0	0.1	0.6	0.4	0.3	0.2	0.2	0.2	0.5	0.6	0.5	0.2	0.5	0.2	0.5	0
C11	0	0.4	0.1	0.1	0.4	0.3	0.5	0.1	0.3	0.1	0	0.4	0.3	0.2	0.1	0.2	0.3	0.3	0.4	0.5	0.1	0.4	0	0.3	0
C12	0.5	0.2	0.6	0.6	0.2	0.3	0.1	0.3	0.3	0.6	0.4	0	0.1	0.7	0.6	0.3	0.3	0.4	0.2	0.3	0.6	0.2	0.4	0.3	0.5
C13	0.4	0	0.4	0.4	0	0	0.1	0.2	0	0.4	0.3	0.1	0	0.4	0.4	0.1	0.2	0	0	0	0.4	0	0.3	0	0.4
C14	0.2	0.7	0.1	0.1	0.7	0.6	0.8	0.4	0.6	0.3	0.2	0.7	0.4	0	0	0.2	0.5	0.4	0.7	0.8	0.1	0.7	0.3	0.6	0.2
C15	0.1	0.6	0	0	0.6	0.5	0.7	0.3	0.5	0.2	0.1	0.6	0.4	0	0	0.1	0.4	0.3	0.6	0.7	0	0.6	0.2	0.5	0.1
C16	0.1	0.2	0.1	0.1	0.2	0.1	0.4	0	0.1	0.2	0	0.3	0.1	0.2	0.1	0	0.4	0	0.2	0.3	0.1	0.2	0	0.1	0.1
C17	0.3	0.4	0.4	0.4	0.4	0.4	0.1	0.4	0.5	0.2	0.3	0.3	0.2	0.5	0.4	0.4	0	0.6	0.4	0.3	0.4	0.3	0.4	0.5	0.2
C18	0.4	0.2	0.3	0.3	0.2	0.1	0.5	0.2	0.1	0.5	0.3	0.4	0	0.4	0.3	0	0.6	0	0.2	0.3	0.3	0.2	0.3	0.1	0.4
C19	0.5	0	0.6	0.6	0	0.1	0.3	0.3	0.1	0.6	0.4	0.2	0	0.7	0.6	0.2	0.4	0.2	0	0.1	0.6	0	0.4	0.1	0.5
C20	0.6	0.1	0.7	0.7	0.1	0.1	0.3	0.4	0.2	0.5	0.5	0.3	0	0.8	0.7	0.3	0.3	0.3	0.1	0	0.7	0	0.5	0.2	0.5
C21	0.1	0.6	0	0	0.6	0.5	0.7	0.3	0.5	0.2	0.1	0.6	0.4	0.1	0	0.1	0.4	0.3	0.6	0.7	0	0.6	0.2	0.5	0.1
C22	0.5	0	0.6	0.6	0	0.1	0.3	0.3	0.1	0.5	0.4	0.2	0	0.7	0.6	0.2	0.3	0.2	0	0	0.6	0	0.4	0.1	0.5
C23	0.1	0.4	0.2	0.2	0.4	0.3	0.5	0.1	0.3	0.2	0	0.4	0.3	0.3	0.2	0	0.4	0.3	0.4	0.5	0.2	0.4	0	0.3	0.1
C24	0.4	0.1	0.5	0.5	0.1	0	0.4	0.2	0	0.5	0.3	0.3	0	0.6	0.5	0.1	0.5	0.1	0.1	0.2	0.5	0.1	0.3	0	0.4
C25	0	0.5	0.1	0.1	0.5	0.4	0.6	0.2	0.4	0	0	0.5	0.4	0.2	0.1	0.1	0.2	0.4	0.5	0.5	0.1	0.5	0.1	0.4	0

In cases where the obtained IFPs are many, it is recommended to combine them into clusters. For this purpose, a neural network of the SOM type was used, the structure of which was described above.

Typically, this data on the input of the neural network is divided into relevant groups according to [8, 9]. This does not always reflect the distribution of the data in the particular case. In this way, the interval in which none of the values fall will be excluded from the total part of the data.

We use a SOM neural network with one input, 6 neurons in layer (Figure 2). This means that the clusters will also be 6.

150 iterations are used for SOM training, and the Matlab function for generating random initial values is used for the initial weight values.

The color-coded figure shows the distance of individual clusters determined by the distances from the weighting coefficients (Figure 3).

In simulation, a different number of input vectors fall into individual clusters, as can be seen in Figure 4.

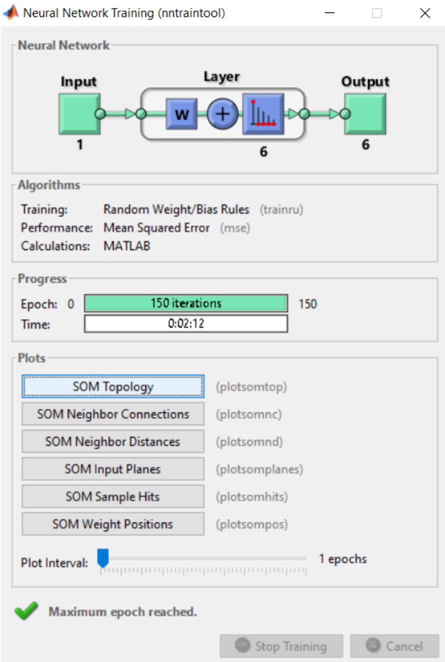

Figure 2. Structure of the SOM neural network

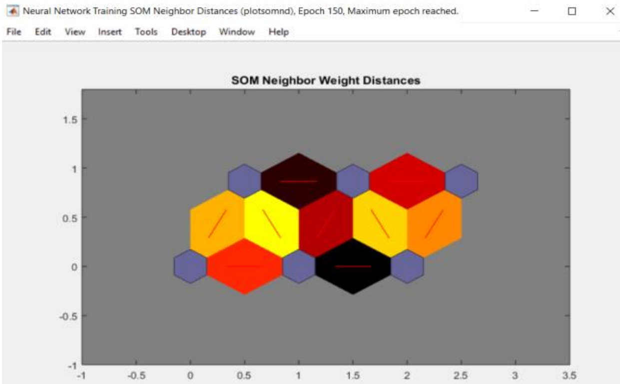

Figure 3. Distances between the weight coefficients

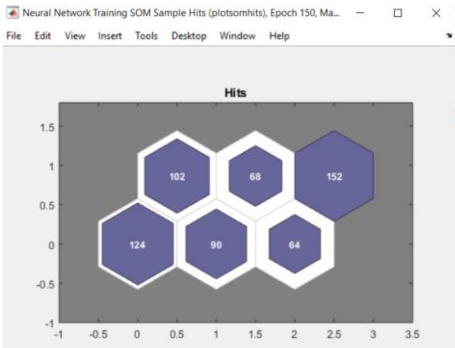

Figure 4. SOM sample hits

In the next Table 3 are given:

- the subsequent number of the cluster;
- the weight coefficients indicating the center of gravity of the cluster;
- the number of input vectors falling into the corresponding cluster.

Table 3. Clustering parameters

Cluster	Center of gravity of the cluster	Number of input vectors
1	0.318652529479714	124
2	0.452795520403604	90
3	0.699530692275647	64
4	0.400405125487479	102
5	0.630847187332542	68
6	0.797252710939742	152

The learning of the SOM was implemented with a full table for membership part of the IFS (600 pairs).

4 Conclusions

In the paper, the level of burnout among the 139 medical employees from 6 medical centers was analyzed. The correlations between different parameters characterizing the respondents were investigated by InterCriteria Analysis method. The obtained 300 IFPs were clustered using an adaptive neural network.

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