Modeling Work Motivation with a Fusion ARTMAP Neural Network

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Abstract
This paper seeks to introduce the ARTMAP family of artificial neural networks as a mathematical theory for modelling work motivation. A new type of construction of psychometric scales based on Fuzzy ART modules is proposed. Psychological relations are modelled with the ARTMAP processing mechanism. Two variations – Fuzzy and Fusion are evaluated with respect to a psychological database. The results achieved are preliminary, but give clear indication of the method's potential. Due to the high precision, capacity for individualisation of the information, and better use of the raw data by Fusion ARTMAP, it can be of much help in organizational research. More specifically, human resources management may benefit from the opportunity to use computer simulations of on-going human interaction processes.
Keywords: Work Motivation, Fusion ARTMAP NN

1 Introduction

In work and organizational psychology (WOP) no sophisticated mathematical theory which could explain the relationships between variables has been developed so far. In order to quantify dependencies in the empirical data, one has to rely on statistics. Today most widely used is linear structural equations modeling. In essence, the researcher devises concepts and puts them into flesh by means of questions, "items" which are believed to carry information of various aspects of one and the same phenomenon.

Next, the psychological variables thus aggregated, are used in structural equations. At this stage linear regression is applied with the idea that the observed population covariance matrix should be preserved as much as possible in the obtained model covariance matrix. This match is measured by a goodness-of-fit criterion. Therefore the main objective is to explain the patterns of covariance observed among the studied variables. As this can be done mathematically in more than one way for a given data sample, many equivalent models can be derived, which differ substantially from each other. In the psychological community this is tacitly perceived as deficiency of the method, and the stress is put on assessing theoretically derived predictions to the data. If a hypothesized model fails, the temptation occurs to look for competing models, a process gracefully called "respecification". Thus, the modeling part of the scientific inquiry gradually becomes data driven and therefore unsatisfactory from methodological point of view.

A recent comprehensive survey (Kelloway, 1996) has summarized these tensions and has shown that the models currently prevailing in the psychological literature are moderately to highly overidentified, and therefore easily disconfirmable. In the pursuit of more reliable methods for data processing, in this paper we investigate the use of ARTMAP neural networks.

2 Applying Neural Networks in Work and Organizational Psychology

The artificial neural networks (ANN) originate partly in psychology, and are statistical in nature. This combination makes them potentially valuable for data processing in the social sciences, where the studied phenomena depend on human behaviour, and usually a strong empirical base is at hand. More specifically, many ANNs can offer nonlinear statistical techniques which capture data variance better than their linear analogues like linear regression, factor analysis, principal component analysis, etc. Therefore applying neural networks to derive statistically valid models and predict data is a natural alternative, and it has already been successfully tried (Wiggins, Engquist, and Looper 1992; Collins and Clark, 1993; Mengov, Zinovieva, Roe, Sotirov, in preparation).

Yet another type of application of ANNs in WOP may be feasible. It should build upon the neurophysiological origin and substrate of certain neural networks, not on pure statistical fundamentals. Baum (in Roy and Levine, 1998) notes that many disciplines have independently concluded that the brain is a multiagent system in which modules with large numbers of neurons interact. He gives a number of examples, among them the following. Evolutionary psychologists use the Wason selection test, psychophysical test of reasoning which seems to indicate that humans have a module specifically for reasoning about social interactions. There is also indirect evidence of a module for resource management etc. From such a perspective the result of applying ANN in organizational psychology can be viewed in a different way than just as a highly under-identified nonlinear statistical model in which statistical validity is difficult, if not impossible to test. The same model can be seen simply as embodying key functional and structural features of the studied phenomena, and therefore, providing a relevant mathematical theory.

One very good example may be found in the ART neural networks. Sarle (1994) notes that ART NN are based explicitly on neurophysiology and defined in terms of detailed differential equations. This is in contrast with most ANNs, which can often be recognised as directly equivalent to various statistical models. ART networks have already been algorithmically implemented using analytical solutions or approximations to these differential equations. Sarle points out cases in which noisy data have perplexed one type of these networks (Fuzzy ART). This, together with the fact that ART does not estimate parameters in any statistical sense makes him conclude that, the whole paradigm is "of doubtful benefit for data analysis". In contrast, we believe that the ART-type networks – with their deep roots in neurophysiology, and their modular structure, – may be quite pertinent if the data is derived from a related area. In this paper we propose to use the ART paradigm as a mathematical model for a problem of work and organizational psychology, namely, investigating relationships in work motivation.

3 A Psychological Interaction Model

Usually, at the initial stage of data processing factor analysis is used. The success of factor specification is measured by the Cronbach alpha. In essence, this is a statistical measure of cohesion or concurrence among the answers of the particular subset of questions that address a psychological concept. If the alpha is low (e. g. below 0.50) the items responsible for its decrease are discarded. Thus the concept's integrity is improved at the expense of its initial theoretical richness. An example of a factor analysis model is shown in Figure 1, where each of three factors F_1,F_2,F_3 is formed by various numbers of items X_1, X_2, ..., X_6. Here $a_1,\ldots, a_6$ are factor loadings for each item, and $e_1,\ldots, e_6$ are errors. This method for data pre-processing is used also in our paper.

An organizational interaction model (Ten Horn, 1989; Zinovieva, Ten Horn, and Roe, 1993) has been developed to study work motivation by the means of a questionnaire. We shall demonstrate the applicability of ART neural networks in work and organizational psychology on a practical example utilizing this model. It contains three groups of psychological variables: characteristics of the work situation as perceived by the staff, personal characteristics of each employee, and personal outcomes. The first two groups are variables, theoretically influencing the third one, as shown in Figure 2.

The questionnaire comprises the following groups:

1) Variables characterising the work situation:

- Opportunities to satisfy needs defined by Maslow (1954): the needs for personal growth, self-esteem, esteem from others, social contacts, belongingness to a group, job security, and physiological needs.

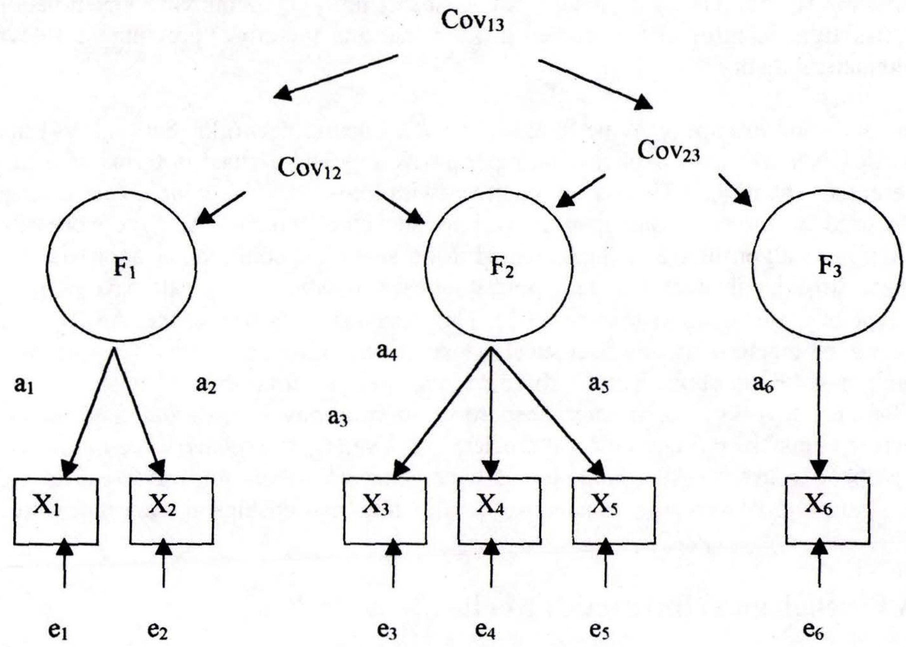

Figure 1: A factor analysis model.

- Job characteristics: task identity, variety, work autonomy, feedback from the work, specialisation, and standardisation.
- Characteristics of the organization: salary, career opportunities, consultative climate, closeness of supervision, work contacts, and informal contacts.

2) Characteristics of the employee: age, gender, education level, and breadwinnership.
3) Personal outcome variables: general job satisfaction, tendency to leave the current job, work-related stress, and work involvement.

The model implies that Work activity (C) depends on the synergy between the characteristics of the work situation (A) and the employees (B). It affects the organisational performance (D), and has impact on the individual (E). This questionnaire addresses only areas (A), (B), and (E). The first problem in this paper is defined as correct grouping of employees with respect to the outcome psychological variables defining the work motivation. Such information is potentially very important for two types of professionals – business decision makers and organizational consultants,

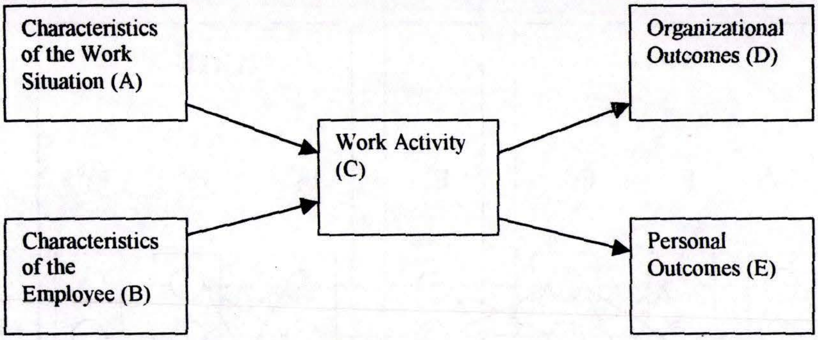

Figure 2: The psychological work model. Each of the modules contains a group of factors obtained with factor analysis. Work activity (C) depends on the synergy between the characteristics of the work situation (A) and the employees (B). It affects the organisational performance (D), and has impact on the individual (E). Adapted with permission from (Ten Horn and Roe, 1992).

involved in organizational change and conflict resolution. In (Mengov, Zinovieva, and Sotirov, 1998) we have shown that area (E) is well predicted using (A) and (B), and also that the interaction model can be substantiated by the Fuzzy ARTMAP neural network by introducing an explicit representation for area (C).

Our second goal is to improve the process of raw data aggregation early on. Instead of variable formation by averaging on all items, which have survived the Cronbach alpha test, we propose to preserve and use them with their original values. This is a totally new concept which embodies Fuzzy ART modules for each of the 25 psychological variables. The modules submit data to the Fuzzy ARTMAP. In essence, this structure implements a Fusion ARTMAP system.

4 Fuzzy ARTMAP and Fusion ARTMAP as Data Processing Tools

The Fuzzy ARTMAP neural network (Carpenter, Grossberg, Markuzon, Reynolds, and Rosen, 1992) is shown on Figure 3. It incorporates several fundamental features which motivate its pertinence in our problem. First, it takes for granted the subjective nature of the data, which makes it particularly useful for processing answers gathered with questionnaires.

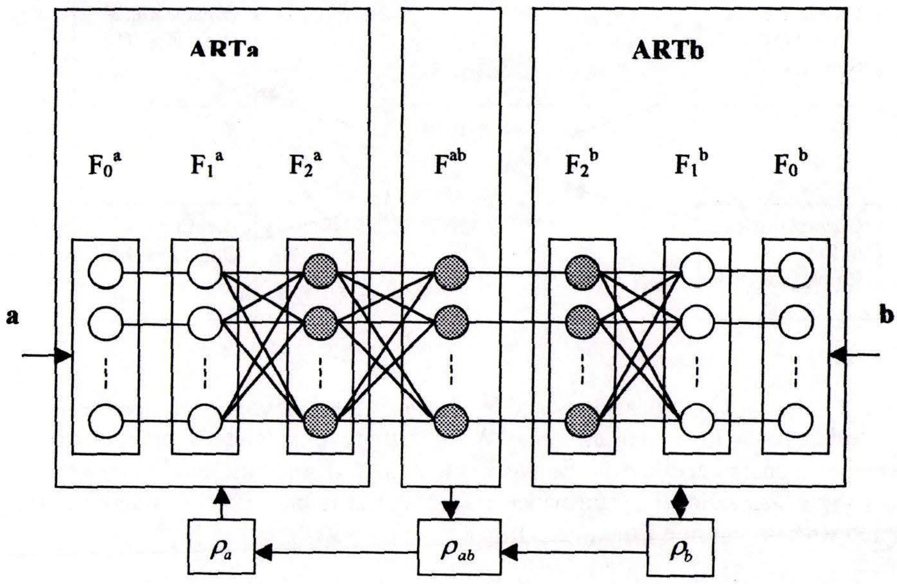

Figure 3: Fuzzy ARTMAP neural network. It may be structurally and functionally mapped onto the psychological interaction model.

This is possible because it embodies a mathematical realisation of the Helmholtz postulate (Helmholtz, 1866, 1896) stating that humans and animals acquire knowledge not by learning information directly from the senses, but by remembering their individual impressions of the received information (Grossberg, 1988). Second, it combines recognition, recall, and reinforcement, and incorporates a mechanism that uses predictive results as feedback in learning (Carpenter et al., 1991). Thus it emulates the evolutionary knowledge acquisition in all living creatures, and is in agreement with the spirit of Pavlovian and Skinnerian conditioning. Third, it embodies functional cognitive hierarchy which allows for gathering memories at various levels of abstraction. And the concepts in work and organizational psychology are generally very abstract. Fourth, the Fuzzy ARTMAP system is cognisant of the novelty of a received input and is able to assimilate while fully preserving all previous knowledge. Thus, a rare but potentially important case can never be omitted. This last property is exceptionally useful in predicting individual responses to work situations in organizational settings.

Fuzzy ARTMAP shares all these characteristics with another neural network - Fusion ARTMAP (Figure 4). In fact there exists a dualism between the two architectures, as each of them can be viewed as special case of the other. Fusion ARTMAP, however, possesses one very attractive feature for our problem – it adaptively classifies patterns from multiple sources (sensors) of information by allotting a Fuzzy ART module to each of them. So, each psychological concept can have a dedicated module accommodating its own subset of items-questions. Now the variable aggregation is completely changed – the pre-processing resulting in averaging on all items is substituted by ART-type processing. In so doing, two benefits are obtained:

1. The information gathered by interviewing subjects is utilised more fully, as the small differences among the items in a variable are preserved. They contain nuances that may be important to the theorist. After the procedure of discarding the inconsistent items, the remaining participate as separate entities in the data processing.
2. Again, the idea of remembering the individual impressions is implemented by the Fuzzy ART modules, this time at the outermost level. The respondent's subjectivity is respected and tolerated to a much higher degree as it contributes to the investigation.

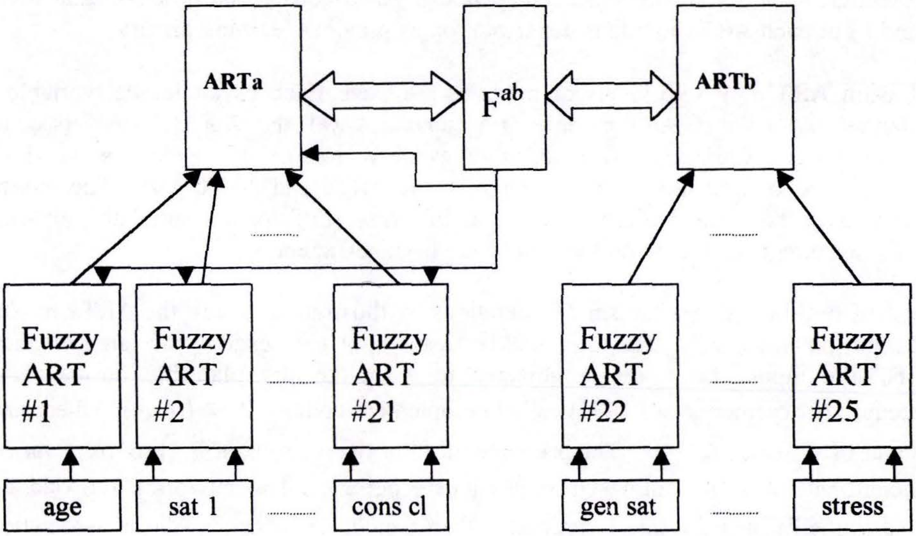

Figure 4: Fusion ARTMAP Neural Network. A number of Fuzzy ART modules aggregate the variables, then submitted to the Fuzzy ARTMAP.

So far we have outlined the methodological grounds for the choice of neural network to process the psychological data. The most attractive feature of Fusion ARTMAP, however, is the opportunity to meaningfully map it onto the interaction model because of three key structural similarities, which the two share.

1. Averaging on items after the factor analysis is paralleled by training Fuzzy ART modules with the same items.
2. The neural network combines two functionally "higher" self-organizing modules ARTa and ARTb, suitable for representing the relatively autonomous groups of organizational and personal characteristics (boxes A and B in Figure 2), and personal outcomes (box E).
3. Both psychological model and Fusion ARTMAP system have essential intermediary blocks – box (C) in Figure 2, and F^{ab} in Figure 4 respectively. To a first approximation, the elements of F^{ab} may be seen as embodiment of the complex relationships between the personal and organizational inputs and the individual outcomes.

The elements' functional operations substantiate the analogy. Perhaps the strongest argument is that for both models the Helmholtz postulate holds by definition. As mentioned, all perceptions registered with the questionnaire of the Figure 2 psychological model are personality-dependent. Analogously, the processing at levels F_1 and F_2 of each ART module is dependent on its previous learning history.

In Fusion ARTMAP two levels of modules are used. Each psychological variable is implanted into a Fuzzy ART module. It accumulates well the subjects' answers coded as real numbers. The outputs from all modules are vectors of '1'-s and '0'-s, which are joint together to form the inputs a and b to the ARTa and ARTb parts. The internal operations in the latter two are the same as in Fuzzy ART for our simulator, although strictly speaking, ART 1 modules would have been sufficient.

We shall outline the mechanism of operations by illustrating it with the ARTa module and input pattern a submitted to it. (ARTb treats input b in exactly the same manner.) At F_0^a the input vector a is subjected to a biologically plausible normalization procedure (Carpenter et al., 1991) called complement coding: $I^a = (a, a^c)$, where each element of a^c is $a_i^c \equiv 1 - a_i$. The presence of I^a in the neurons of F_1^a provokes various associations at level F_2^a, all based on previous experience. The network's knowledge is linked to the F_2^a neurons and contained in their weight vectors w_j^a. All the associations enter a competition, whose objective is to find the best possible matching to the received input. Each neuron in F_2^a layer receives excitatory signal $T_j^a(I^a)$ of the form:

$$T_j^a(I^a) = \frac{\left|I^a \wedge w_j^a\right|}{\alpha + \left|w_j^a\right|}. \tag{1}$$

Here α is a parameter normally approaching zero. The symbol $\wedge$ designates the Fuzzy AND operator. The competition is won by the association (carried by one F_2^a neuron) that has received the largest signal $T_J^a(I^a)$, where:

$$T_J^a(I^a) = \max\{T_j^a(I^a) : \forall j\}. \tag{2}$$

Next, the winner J with weight vector w_J^a is matched at F_1^a against the received signal I^a:

$$\frac{\left|I^a \wedge w_J^a\right|}{\left|I^a\right|} \geq \rho_a. \tag{3}$$

Coefficient ρ_a, known as vigilance parameter for ARTa, has value between 0 and 1, and serves as criterion for the degree of similarity between received information and invoked association. If (3) is not satisfied, the F_2^a neuron J is suppressed until the end of processing of the current pattern I^a, and a new competition cycle follows. Possibly after several trials with different associations, one will successfully pass the test of (3). Its carrier – the neuron at F_2^a with weight vector w_J^a will be modified to assimilate the new information. This is done according to

$$w_J^{a(new)} = \beta\left(I^a \wedge w_J^{a(old)}\right) + (1-\beta)w_J^{a(old)}, \tag{4}$$

where β is learning rate parameter. If no suitable association is found, pattern a itself becomes the founder of a new one. Thus, the respondents' perceptions forming the psychological variables in both left and right side of the model in Figure 2 are coded in the connection weights w^a and w^b of ARTa and ARTb respectively. In this way ARTMAP parallels the structure of the questionnaire and can serve as reasonable operational model for our work-and-organization-psychology concepts.

The inter-ART operations and the input-output interaction in the WOP model substantiate another functional analogy. The scheme from Figure 2 serves as basis for a rather broad and general survey of the studied organization by a large set of variables and items (Ten Horn and Roe, 1992). Next, on the basis of this generic picture, a concrete regression model showing the interaction of independent (A & B) and dependent (E) variables is developed. All statistically significant connections form a diagnostic model. Changing parameters such as confidence level, target value for the goodness-of-fit, etc. can lead to radically different path diagrams. In all of them the knowledge about the Work Activity (C) is to be found only in the structure of the connections and path coefficients. Thus it remains implicit, and its validity is determined by the limitations of the regression method. In contrast, the ARTMAP system has a distinct component – neuron layer F^{ab} with connection weights w^{ab} - for coding the input-output associative memory and a mechanism for its operation. In the later, key role is played by vigilance parameters ρ_a, ρ_b, and ρ_{ab}. Inter-ART vigilance ρ_{ab} takes care for the correct linkage between F_2^a and F_2^b. For full description see (Carpenter et al., 1991). While training is on, the neural network learns incrementally, i.e., on a trial-by-trial basis to accumulate each (A & B) pattern into ARTa, and its (E) counterpart into ARTb, as well as to associate the relevant neurons with each other via F^{ab} and w^{ab}.

Often in medical, psychological, and social databases the problem with inconsistent input-output patterns occurs. In our case it comprises the appearance of two identical (A & B) patterns, associated with differing (E) patterns. To the network it looks like submitting the answers of one and the same respondent whose outcome variables for some reason are contradictory. Therefore strict many-to-one matching of the category nodes of the ARTa and ARTb nodes must be observed. The category formation process is largely governed by the ρ_b vigilance parameter, which causes ρ_a to rise and "impeach" the active category at F_2^a. If ARTa experiences a perfect match, its vigilance parameter is required to grow above 1, which is not allowed by the network's design principles. To avoid this conflict we have modified the algorithm to create a new pair of neurons-categories at the two modules, which accounts for the second of the two input-output patterns with identical left parts. This technique is equivalent to the following heuristic rule (Lim and Harrison, 1997):

$$0 \le \rho_a \le \min\left(1, \frac{\left|I^a \wedge w_J^a\right|}{\left|I^a\right|} + \delta\right). \qquad (5)$$

This ensures unconditional assignment of a new set of ARTa, F^{ab}, and ARTb neurons-categories whenever data inconsistency occurs.

The advantage of Fusion ARTMAP over the Fuzzy version is that it allows only part of the input to the ARTa module to be corrected in case of wrong prediction during learning. Thus only some of the psychological variable inputs are prompted to change which gives greater functional flexibility to the data processing instrument.

One additional advantage of the use of an ARTMAP system is in its augmenting the original methodology by adding feedback from the Personal Outcomes (E), e. g., general satisfaction, work-related stress, etc. to Work Activity (C) and back to the personal and organizational characteristics. This is obvious in the psychological science, but so far has not been accommodated in the Figure 2 model with its unidirectional connections.

5 Experimental Results with the WOP Database

It was discussed previously that in many areas of organizational research there is not enough knowledge to specify a reliable model structure. Naturally, predictions will have limited success no matter how rich the empirical data might be. The case we are presenting is taken from a survey among 1062 Bulgarian industrial employees, who answered the questionnaire. As it contained 270 questions, not all of them were given answers. All cases with missing values concerning the 21 input variables and the 4 outcome variables were discarded. Then the prediction-oriented experiments were carried out with the remaining 348 subjects. This sample was divided into derivation/training set (241 cases) and validation set (107 cases). For more detail on the measurement instrument and the results obtained with the traditional linear structural modeling see (Zinovieva et al., 1993). In Table 1 we present only figures for the correlation coefficient obtained with linear regression.

Correlation Coefficient	General Satisfaction	Tendency to Leave	Work Involvement	Work-related Stress
for derivation sample of 241 subjects	0.5702	0.5955	0.4687	0.5437
for validation sample of 107 subjects	0.5175	0.5391	0.2875	0.4905

Table 1. Results obtained with linear regression analysis.

These regression results are typical of such studies. They reflect not only the major weakness of the linear methods – the insufficient amount of variance accounted for, but also the state of theoretical advancement in the area of organizational research. The later fact implies an inevitable upper limit to the predictive success of any mathematical method.

It is not possible to compare the results obtained with regression and an ARTMAP neural network directly. The former provides explicit prediction of the outcome variables, while the later groups individuals into clusters with respect to the same outcomes using them only implicitly. Tables 2 and 3 display some interesting results about the performance of Fuzzy ARTMAP and Fusion ARTMAP. The first four columns give the initial conditions at which the networks have been trained.

Vigilance ρ_a	Vigilance ρ_b	Learning rate β	Training epochs	Categories in ARTa	Categories in ARTb	Correctly classified, training set (n=241)	Correctly classified, test set (n=107)
0	0.6	1	5	26	10	0.494	0.374
0	0.8	0.9	5	53	35	0.639	0.112
0	0.8	1	5	69	40	0.793	0.090
0	0.8	1	1	66	40	0.760	0.080

Table 2. Correct classification of subjects by four different Fuzzy ARTMAP networks.

Vigilance ρ_a	Vigilance ρ_b	Learning rate β	Training epochs	Categories in ARTa	Categories in ARTb	Correctly classified, training set (n=241)	Correctly classified, test set (n=107)
0	0.9	0.95	5	47	37	0.555	0.626
0	0.95	0.95	5	51	42	0.463	0.551
0	0.9	0.95	1	40	28	0.430	0.262
0	0.97	0.95	1	67	47	0.186	0.178

Table 3. Correct classification of subjects by four different Fusion ARTMAP networks.

The experimenter is able to influence the process of category (cluster) formation via the parameter choice, especially vigilances ρ_a, and ρ_b. Varying the former is less important (cf. Carpenter et al., 1991), while the later has direct impact on the category formation and refinement. Low ρ_b leads to small number of more general categories, while higher values of ρ_b cause great number of select categories. The values which guarantee the best forecasts can vary in large intervals and are found experimentally for each case of application. The last four columns in the two tables contain the experimental results. Based on their personal characteristics and responses to their work situations, all subjects are grouped in ARTa and ARTb categories. The former are associated with blocks (A) and (B) from the interactional model, the later match block (E). It is the ARTb categories that are important for the organizational theorist because they are formed with respect to the motivational outcomes.

In (Mengov et al., 1998) we have shown that with a small number of clusters, usually 3-4, the prediction rate of Fuzzy ARTMAP stays within 85-95%. This is fairly high for predicting human perceptions of satisfaction, stress, work involvement, and tendency to leave a job. The number of clusters however, might be insufficient for a number of potential practical applications. One such application might be in organizational change and/or restructuring, where the motivational outcomes of the employees will be evolving side-by-side with the observed developments. It might be desirable to monitor these alterations and, based on the employees' responses, to predict potential aggravation of conflicts. To this end a much more subtle structure of clusters will be needed. Indeed, for the human resources managers or organizational consultants it will be much more informative to observe e.g., changes in the tendency to leave the job in employees moving across various subsets of 20-30 clusters instead of only 3-4 coarse categories. With the objective to understand how this can be achieved, here we test both Fuzzy and Fusion variations of ARTMAP for correct grouping with a large number of clusters – above 10, but preferably 30 – 50. In Tables 2 and 3 the networks are placed in descending order of their classification success with the test set of 107 subjects. The best Fusion ARTMAP network (first row in Table 3) has predicted correctly the cluster membership of 55.5% of all 241 subjects from the training set, and of 62.6% from the test set. To put these figures in the right perspective one has to understand that the network had to choose 1 of 37 ARTb categories in which to put a respondent, and in more than half of all cases it has made the exact choice. This result may be paralleled with a Fuzzy ARTMAP network (second row in Table 2) where the choices have been 35 in number. Only 11.2% of the unknown subjects have been correctly classified. Further experimenting showed that with a small number (3-4) of ARTb clusters Fuzzy ARTMAP is superior in correct classification of unknown subjects. As seen also from Tables 2 and 3, there is a superiority of Fusion over the Fuzzy version of ARTMAP at the end of proliferating clusters. Two factors account for it. First, more information is lost at the pre-processing stage where variables are aggregated towards Fuzzy ARTMAP, than the ART-type pre-processing of the Fusion ARTMAP. Second, the later network has Fuzzy ART modules containing a variety of images for each theoretical concept (input variable) which gives the ARTb module extra flexibility to find the exact match to a subject. In contrast, Fuzzy ARTMAP has to work with ARTb vectors of fixed values for their components.

6 Conclusions

In this paper the Fusion ARTMAP neural network is applied in the pursuit to contribute to the methodology of organizational research. A new type of psychological scaling is introduced which utilises all the items-questions initially used to construct a concept according to the theoretical reasoning. To this end certain ideas of Helmholtz and Grossberg available in mathematical form are indirectly exploited. This in turn, has allowed to look at the neural networks as a tool which to a degree provides a pertinent mathematical model, and prevents data-driven reasoning. Two ARTMAP architectures – Fuzzy and Fusion, have been compared and their areas of better performance have been identified for the specific problem. A next step will be to strengthen the predictive power of the method by identifying in greater detail the patterns of interaction of the numerous controlling parameters. In the future this work may be continued in two directions. One is to help business decision makers and organizational consultants in monitoring and solving problems of conflict resolution in organizational development.

The second direction might be to discover better mathematical models for the domain of organizational research.

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