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Short Communication

Neuro-fuzzy modelling in support of knowledge management in social regulation of access to cigarettes by minors

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Abstract

In this paper a neuro-fuzzy modelling is proposed to support knowledge management in social regulation. The neuro-fuzzy learning process is based on tacit knowledge in order to highlight what specific steps local government should undertake to reach the outcome with an increase in compliance. An example is given to demonstrate the validity of the approach. Empirical results show the dependability of the proposed techniques.

Keywords: Neuro-fuzzy; Knowledge management; Social regulation

1. Introduction

Knowledge could be understood for social regulation purposes as explicit and tacit [1]. Explicit knowledge relates to the community culture indicating how things work in the community based on social policies and procedures. Tacit knowledge is ethics and norms of the community. The former could be codified, stored and transferable in order to support decision making, while the latter being based on personal knowledge, experience and judgments is difficult to codify and store. However, since the tacit knowledge is expressed mainly through linguistic information, it can be stored and, therefore, support the knowledge management in social regulation through the application of neuro-fuzzy systems [2].

The neuro-fuzzy approach is based on the integration of artificial neural networks (ANNs) and fuzzy inference systems (FISs) [3]. Applied in social regulation the neuro-fuzzy model creates *if–then* fuzzy rules, which are easy to comprehend because of its linguistic terms. The paper provides the neuro-fuzzy learning process based on tacit knowledge in order to highlight what specific steps local government should undertake to reach the outcome with an increase in compliance. The paper is divided as follows: part two defines what has been done so far in order to reduce the rate of regular smoking among young people. Part three relates to neuro-fuzzy models application to easily supervise the learning process of adjusting governmental parameters to reach the expected outcomes. Part four illustrates the application of Tagaki-Sugeno Kang and Mamdani neuro-fuzzy models based on data provided by local governments. The paper ends with concluding remarks.

2. Social regulation of access to cigarettes by minors at present

Tobacco smoking is associated with addiction to the nicotine content of cigarette smoke. Recruitment of minors as smokers is dependent on access to cigarettes. The societal objective of social regulation of the regulation of access by minors to cigarettes, expressed as public policy, is reduced incidence of smoking related ill-health and premature death. Tutt et al. [4] report on a six-year project commenced in 1993 in New South Wales. The relevant legislative provisions which did not change significantly during the period reported, made it an offence for a person or their employee to sell tobacco to a person under 18 years of age. The initial intervention relied entirely on publicity and education of both suppliers

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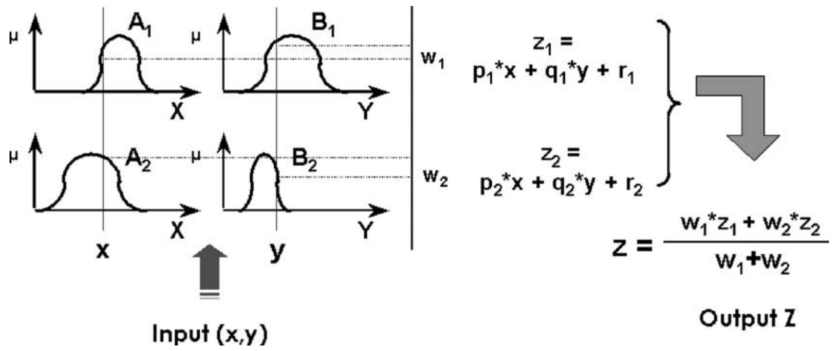

Fig. 1. TSK type fuzzy inference system.

and minors and others who were potential consumers of tobacco products.

A different, comparative project was conducted in six local government areas (LGAs) of Melbourne in 1998 and 1999. Different regimes of education, enforcement and media reporting of successful prosecutions were applied and the effects on access by minors assessed [5,6].

3. Neuro-fuzzy support of social regulation

A FIS can utilize human expertise by storing its essential components in rule base and database, and perform fuzzy reasoning to infer the overall output value. ANN learning mechanism does not rely on human expertise. Due to the homogenous structure of ANN, it is hard to extract structured knowledge from either the weights or the configuration of the ANN. The weights of the ANN represent the coefficients of the hyper-plane that partition the input space into two LGAs with different output values. If we can visualize this hyper-plane structure from the training data then the subsequent learning procedures in an ANN can be reduced. However, in reality, the a priori knowledge is usually obtained from human experts and it is most appropriate to express the knowledge as a set of fuzzy *if–then* rules and it is not possible to encode into an ANN. Since the drawbacks pertaining to these two approaches seem complementary, we have built an integrated system combining the concepts of FIS and ANN modelling. We used adaptive network based fuzzy inference system (ANFIS) that implements a Takagi Sugeno Kang (TSK) FIS [6] and an evolving fuzzy neural network (EFuNN) implementing a Mamdani FIS [3]. For a first order TSK model as shown in Fig. 1, a common rule set with two fuzzy *if–then* rules is represented

$$\text{Rule 1: If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1$$

$$\text{Rule 2: If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2$$

where x and y are linguistic variables and A_1, A_2, B_1, B_2 are corresponding fuzzy sets and p_1, q_1, r_1 and p_2, q_2, r_2 are linear parameters.

TSK fuzzy controller usually needs a smaller number of rules, because their output is already a linear function of the inputs rather than a constant fuzzy set [3].

For a Mamdani inference system (Fig. 2) the rule consequence is defined by fuzzy sets and has the following structure.

$$\text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } z_1 = C_1$$

ANFIS makes use of a mixture of backpropagation to learn the premise parameters and least mean square estimation to determine the consequent parameters. A step in the learning procedure has two parts: in the first part, the input patterns are propagated, and the optimal conclusion parameters are estimated by an iterative least mean square procedure, while the antecedent parameters (membership functions) are assumed to be fixed for the current cycle through the training set. In the second part, the patterns are propagated again, and

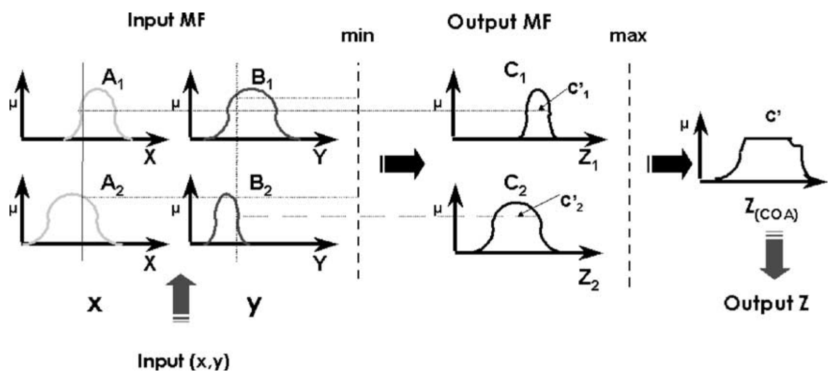

Fig. 2. Mamdani fuzzy inference system.

Table 1
Performance comparison between ANFIS and EFuNN

LGA	ANFIS training					EFuNN training		
	Time	Trg RMSE		Test RMSE		Time	Trg RMSE O/P 1 and 2	Test RMSE O/P 1 and 2
		O/P 1	O/P 2	O/P 1	O/P 2			
1	58	1.2×10^{-4}	5.0×10^{-5}	0.034	2×10^{-4}	4	7.3×10^{-3}	0.2201
2	54	0.0011	1.9×10^{-4}	0.058	0.032	3	9.2×10^{-3}	0.421
3	54	0.0011	1.9×10^{-4}	0.058	0.032	3	9.2×10^{-3}	0.421
4	52	3.3×10^{-4}	1.6×10^{-4}	0.044	0.031	3	5.2×10^{-3}	0.429
5	50	3.1×10^{-4}	1.5×10^{-4}	0.027	0.010	4	0.0317	0.653
6	56	8.0×10^{-4}	5.1×10^{-3}	3×10^{-5}	0.040	4	0.045	0.566

in this epoch, backpropagation is used to modify the antecedent parameters, while the conclusion parameters remain fixed. This procedure is then iterated [7].

EfuNN implements a Mamdani type FIS and all nodes are created during learning. The nodes representing membership functions (MF) can be modified during learning. Each input variable is represented here by a group of spatially arranged neurons to represent a fuzzy quantization of this variable. New neurons can evolve in this layer if, for a given input vector, the corresponding variable value does not belong to any of the existing MF to a degree greater than a membership threshold. A new fuzzy input neuron, or an input neuron, can be created during the adaptation phase of an EFuNN. In case of 'one-of-n' EFuNNs, the maximum activation of a rule node is propagated to the next level. Saturated linear functions are used as activation functions of the fuzzy output neurons. In case of 'many-of-n' mode, all the activation values of rule nodes that are above an activation threshold are propagated further in the connectionist structure [8].

4. Neuro-fuzzy model evaluation and experimentation results

Simulations are done with the data provided from the Government for the six LGAs of Melbourne. Each data set was represented by three input variables and two output variables. The input variables considered were compliance rate by retailers, enforcement according to protocol and community education. The corresponding output variables were compliance rate by retailers and compliance rate by retailers projected as estimated rate of smoking uptake by minors. Seventy percent (random) of each data for training and 30 per cent (random) for testing were used. That is, the neuro-fuzzy models ANFIS and EFuNN were first trained on 70 per cent data. Then it is tested on 30 per cent data.

4.1. ANFIS training

Two Gaussian MF attached to each input variables were applied. Six rules were learning based on the training data for each of the six LGAs. The training was terminated after 1000 epochs. Training performance is reported in Table 1.

4.2. EFuNN training

Three Gaussian MF for each input variable were used as well as the following evolving parameters: sensitivity threshold Sthr $= 0.99$, error threshold Errthr $= 0.001$ and learning rates for first and second layer $= 0.01$. EFuNN uses a one pass training approach. The network parameters were determined using a trial and error approach. Online learning in EFuNN resulted in creating 20 rule nodes. Training results are summarized in Table 1.

4.3. Test results

The test results for all six LGAs using ANFIS and EFuNN are depicted in Table 1. As evident from the results, ANFIS performed better than EFuNN in terms of performance error. However, EFuNN has outperformed ANFIS in terms of computational time.

5. Conclusions

In this paper the neuro-fuzzy support of knowledge management in social regulation was investigated. That is, the explicit knowledge based on social policies and procedures to reduce smoking among youngsters, but also the tacit knowledge expressed through the applied MF. Empirical results show the dependability of the proposed techniques.

Neuro-fuzzy systems make use of linguistic knowledge of FIS and the learning capability of neural networks. Thus we are able to precisely model the uncertainty and imprecision within the data as well as to incorporate the learning ability of neural networks. Compared to neural networks, an important advantage of neuro-fuzzy systems is its reasoning ability (*if–then* rules) of any particular state.

ANFIS performed better than EFuNN in terms of performance error with a compromise on time. EFuNN performed approximately 12 times faster than ANFIS. Hence where performance speed is the criterion EFuNN sounds to be the ideal candidate. As EFuNN uses a one pass training approach it is also suitable for online learning of new data sets. In policy analysis, these computational time differences are of no practical significance.

An important disadvantage of ANFIS and EFuNN is the determination of the network parameters like number and type of MF for each input variable, MF for each output variable and the optimal learning parameters.

As a future research, the selection of optimal parameters will be formulated as an evolutionary search to make the neuro-fuzzy systems fully adaptable and optimal according to policy makers' requirements, by providing analysis of the relative effects of available social regulation measures on smoking rates.

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