

NON-LINEAR HEBBIAN LEARNING ALGORITHM FOR INTUITIONISTIC FUZZY COGNITIVE MAPS IN PREDICTIVE MODEL

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ABSTRACT. Fuzzy cognitive map is a tool which establishes the causal relation between the factors of decision-making problem. It is very instrumental in modelling complex system with expert's opinion, but the confinement of the expert's opinion to crisp values makes the scenario unrealistic. To overcome such conflicts of pragmatic representations, intuitionistic fuzzy cognitive maps with membership and non-membership association weights of the factors are used. In this research work a new approach of non-linear Hebbian learning algorithm to handle intuitionistic fuzzy cognitive maps is initiated, based on this approach anxiety predictive model is proposed. In the field of psychoanalysis, the word anxiety occupies a prime position as many researchers find that the rate of people getting affected by this disorder is increasing due to various peripheral and intramural factors. This work aims in finding the factors contributing to anxiety disorder and this modelling approach will certainly assist in planning and administering appropriate treatment to the victim.

1. INTRODUCTION

Anxiety is a normal and often healthy emotion, however when a person regularly feels disproportionate levels of anxiety, it might become a medical disorder which is characterized by feeling of worry, anxiety or panic that are affect their regular activities. In a recent study, experts alarmed that, even spending too

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much time on mobile phones causes stress and results in anxiety. The various factors that cause anxiety are also explored by many researchers, but still the factors that have major influences have to be discovered by employing scientific decision-making tools. One such kind is Fuzzy Cognitive Maps (FCM), which plays a vital role in many areas such as social, political sciences, engineering, medicine, education, robotics and other areas of science and technology.

Political scientist Robert Axelrod (1976) introduced cognitive Maps in 1970's for representing social scientific knowledge. This cognitive map is a kind of directed graph which establishes relationship between the factors that are expressed as nodes. Cognitive Maps are applied to various research domains as well as it describes expert's perceptions on complex social systems. This was further extended to Fuzzy Cognitive Maps by Kosko [7] and the values from $[-1, 1]$ are assigned as the weightage of the edges. These FCM models are explored by other researchers based on the needs of the decision makers to tackle the uncertainty and ambiguity that characterises human cognitive and reasoning process.

Fuzzy cognitive maps are the effective structures to stimulate such processes. A limitation of current FCM is that they are unable to simulate the hesitancy model due to certain imperfect aspects, incomplete information and impreciseness in decision making situations. To handle such circumstances we propose the extended model of FCM which is based on the theory of Intuitionistic fuzzy sets. This model is robust in nature as it enables the estimation of hesitancy at the output through this work; the nonlinear Hebbian algorithm is used for Intuitionistic Fuzzy Cognitive Maps (IFCM) to know the reasons with high influence for anxiety [1, 10]. This predictive model is recommended to determine the causes with high influence of any crisis, to validate the proposed model, anxiety predictive model is framed which acts as a guide to determine and plan the remedial methods for preventing and detecting the anxiety.

Other valuable references on the topic are [2–6, 8, 9].

2. PRELIMINARIES

This section contains the prerequisite definitions pertaining to this research work.

Definition 2.1. Fuzzy Set: Let X be the universal set. The membership function is denoted by $\mu(A)(x)$ and is defined as $\mu(A)(x) : X \rightarrow [0, 1]$ where $\mu(A)(x) \in [0, 1]$. A is completely characterised by the set of Pairs $A = \{X, \mu(A)(x), x \in X\}$.

Definition 2.2. Intuitionistic Fuzzy Set: Given a universe of discourse E as IFS is defined as $A = \{X, \mu(A)(x), \gamma_A(x)/x \in E\}$, $\mu(A)(x) : E \rightarrow [0, 1]$ and $\gamma_A(x) : E \rightarrow [0, 1]$ define the degree of membership and non membership respectively for every $x \in E$, $\mu(A)(x), \gamma_A(x) \in [0, 1]$ and $\mu(A)(x) + \gamma_A(x) \in [0, 1]$. For $x \in E$ if $\gamma_A(x) = 1 - \mu(A)(x)$. The hesitance of the element $X \in E$ to the set $A \subseteq E$ is defined as $\pi_A(x) = 1 - \mu(A)(x) - \gamma_A(x)$.

Definition 2.3. Intuitionistic Fuzzy Cognitive Maps (IFCM): IFCMS include the intuitionistic fuzzy sets (IFS) to handle the expert's hesitancy in their judgments. The conventional FCM is improved by intuitionistic theory to handle the hesitancy.

Fuzzification and Defuzzification processes: The process of converting a crisp set to a fuzzy set and the reverse process refers to the later.

3. NONLINEAR HEBBIAN LEARNING ALGORITHM

Hebbian learning modules facilitate the handling of unsubstantiated data in the initial phase of artificial neural networks. The transmission of signals from presynaptic and postsynaptic nodes towards a the point of dispensation of a neural network is represented by the following equation $\Delta w_{ij} = \eta y_i(n) x_j(n)$, here y_i, x_j are defined by presynaptic and postsynaptic and is a positive constant that determine the rate of learning.

The above rule is modified and enhanced by Oja to compute solutions to the problems dealing with stability. The generalized Hebbian rule or Oja rule is stated as $\Delta w_{ij} = \eta y_i(n) / (x_j(n) - y_i(n) w_{ij}(n))$. Non Linear Hebbian learning algorithm is one of the four classifications of Hebbian learning algorithm and it was proposed by Papageorgiou non linear Hebbian learning algorithm which is characterized as

$$(3.1) \quad W_{ij}^{t+1} = w_{ij}^t + \eta A_j^t (A_i^t - A_j^t w_{ij}^t),$$

where η is the learning rate. [10]. The extended version to find the new weights and the termination criteria is represented below

$$(3.2) \quad W_{ij}^{t+1} = w_{ij}^t + \eta A_j^t (A_i^t - \text{sgn}(w_{ij}^t) A_j^t w_{ij}^t).$$

The two criteria is of the form

$$F_1 = \sqrt{\sum_{i=1}^n (OC_i^t - T_i)^2}, \quad F_2 = |OC_i^{t+1} - OC_i^t| < e,$$

where OC_i^t is the i th output concept at iteration t and T_i , is the target value, the concept lies in the range of $[T_i^{\min}, T_i^{\max}]$ and the value of $T_i = T_i^{\min} + T_i^{\max} / 2$.

Based on (3.1) and (3.2), the calculation of weights in handling the intuitionistic data is presented below. Using non - linear Hebbian learning algorithm for intuitionistic fuzzy cognitive maps the value of weight w_{ij}^k is calculated in the learning parameter μ :

$$(3.3) \quad w_{ij}^{(k)} = (w_{ij}^{(\mu)} + \mu(\Delta A_i^t \Delta A_j^t - w_{ij}^{(\mu)}), w_{ij}^{(\pi)} + \mu(\Delta A_i^t \Delta A_j^t - w_{ij}^{(\pi)}),$$

and at each step the value of A_i is computed:

$$(3.4) \quad A_i^{t+1} = f(A_i^t + \sum_{i,i \neq j}^N W_{ji}^\mu (1 - w_{ji}^\pi) A_j^t).$$

4. ANXIETY PREDICTIVE MODEL USING NON LINEAR HEBBIAN ALGORITHM

Based on the expert's opinion the factors causing anxiety are presented as follows

- C1. High Disproportionate uplift.
- C2. Exasperation.
- C3. Deficit of concentration.
- C4. Grumpiness.
- C5. Exudation.
- C6. Irrational fears.
- C7. Avoidance of social situation.
- C8. Feeling annoyed.
- C9. Hyperventilation.
- C10. Trouble sleeping.

The primary intuitionistic weights W^0 are given by the experts and the output of the frame works are decided

$$\begin{pmatrix} (0,0) & (0,0) & (.3,.2) & (0,0) & (0,0) & (0,0) & (.4,.1) & (0,0) & (0,0) & (.4,.2) \\ (.4,.1) & (0,0) & (0,0) & (.3,.2) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (.5,.3) \\ (0,0) & (.3,.1) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) \\ (0,0) & (.4,.2) & (.3,.2) & (0,0) & (0,0) & (0,0) & (.2,.3) & (0,0) & (0,0) & (0,0) \\ (0,0) & (0,0) & (.4,.1) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) \\ (.4,.3) & (0,0) & (.5,.2) & (0,0) & (.6,.3) & (0,0) & (0,0) & (0,0) & (0,0) & (.3,.3) \\ (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (.4,.1) & (0,0) & (0,0) \\ (0,0) & (.3,.2) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (.5,.4) \\ (0,0) & (.3,.1) & (0,0) & (0,0) & (.3,.2) & (0,0) & (0,0) & (0,0) & (0,0) & (0,0) \\ (0,0) & (0,0) & (0,0) & (0,0) & (0,0) & (.3,.2) & (0,0) & (0,0) & (.3,.2) & (0,0) \end{pmatrix}$$

The first numerical values employed in the simulation process are

$$A_0 = \{0.4, 0.3, 0.5, 0.2, 0.4, 0.3, 0.2, 0.6, 0.5, 0.7\}$$

and at each step the value of A_i and w_{ij}^k is computed using (3.3) and (3.4).

The above steps are repeated until consistent values are obtained. Compute F_1 and F_2 until final weights are determined. The experts acknowledged region for anxiety lies between 0.71 and 1. Based on the final weights of the factors represented below, the core factors of anxiety are determined.

$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$
0.632	0.685	0.678	0.561	0.654	0.599	0.574	0.654	0.656	0.775
0.716	0.737	0.768	0.659	0.746	0.672	0.681	0.683	0.684	0.829
0.742	0.765	0.797	0.684	0.77	0.69	0.71	0.694	0.693	0.849
0.748	0.774	0.805	0.691	0.776	0.695	0.718	0.691	0.693	0.855
0.751	0.777	0.808	0.693	0.779	0.697	0.721	0.691	0.697	0.856
0.752	0.779	0.81	0.694	0.778	0.698	0.723	0.692	0.698	0.856
0.753	0.78	0.811	0.695	0.779	0.699	0.724	0.693	0.699	0.857
0.753	0.782	0.811	0.695	0.778	0.699	0.725	0.693	0.699	0.857

5. RESULTS AND DISCUSSION

All the ten concepts are considered as factor contributing to anxiety disorder by the experts. The initial representation by intuitionistic fuzzy sets is the realistic presentation of the expert's opinion. In this problem the concept $C11$ has been considered as decision output based on experts view and could be categorized as ALT - Always time. B) AT- At a time C) CN -Certainly not which takes

the range of the values like ALT is 0.71 to 1 AT is 0.41 to 0.7 and CN 0 to 0.40 respectively. For this IFCM Model of the anxiety problem the values of the factors were changed concurrently at the same time and referred as an iteration step. Here the concept C1, C2, C3, C7, C10 have very high influence on the output which is always possible for the anxiety disorder. After profound analysis of the results the factors Exasperation, Deficit of concentration, avoidance of social situation, trouble sleeping are the main reasons for anxiety disorder.

6. CONCLUSION

Non-linear Hebbian algorithm with intuitionistic representations for designing a predictive model is a novel endeavour in this research work. This predictive model can be applied to determine the core causes of any other crisis. This tool can be used to handle managerial decision making scenarios. This model is highly beneficial and compatible in making concrete decisions. One of the significant features of this model is hesitancy tackling competence. The same predictive model can be extended to neutrosophic representations with the incorporation of indeterminacy.

REFERENCES

- [1] A. KANNAPPAN, A. TAMILARSI, E. I. PAPAGEORGIOU: *Analyzing the performance of fuzzy cognitive maps with nonlinear Hebbian learning algorithm in predicting autistic disorder*, J. of App. Math., **5** (2010), 1282–1292.
- [2] J. AGUILAR: *A survey about fuzzy cognitive maps papers*, International journal of computational cognition, **3** (2005), 33–44.
- [3] J. A. DICKERSON, B. KOSKO: *Virtual worlds as fuzzy cognitive maps*, Presence, **3**(2) (1994), 173–189.
- [4] GRAYSTEVEN, ERINZANRE, S. R. J. GRAY: *Fuzzy cognitive maps as representation of mental model and group beliefs*, Fuzzy cognitive maps for applied sciences and engineering, **5** (2014), 29–48.
- [5] S. HAYKIN: *Neural networks: A Comprehensive foundation*, Prentice hall, 1999.
- [6] A. KAUFMAN: *Introduction to the theory of fuzzy subsets*, Academic Press, 1973.
- [7] B. KOSKO: *Fuzzy cognitive maps*, International journal of Man-Machine studies, **5** (1988), 62–75.
- [8] E. I. PAPAGEORGIOU, C. D. STYLIOU, P. P. GROUMPOS: *Fuzzy cognitive map learning based on nonlinear Hebbian rule*, Soft computing journal, **63** (2003), 254–266.

- [9] E. I. PAPAGEORGIOU, C. D. STYLIOU, P. P. GROUMPOS: *Unsupervised learning techniques for fine-tuning fuzzy cognitive map casual links*, Soft computing journal, **64**(8) (2006), 727–743.
- [10] G. A. PPAKOSTAS, A. S. POLYDOROS, D. E. KOULOURIOTIS, V. D. TOURASIS: *Trin- ing fuzzy cognitive maps by using Hebbian learning algorithms: A comparative study*, New publ. house, 2017.
- [11] D. SIVABALASELVAMANI, A. S. HRAISANKAR, L. RAHUNATHAN, A. TAMILARASI: *Ac- cident Identification using fuzzy cognitive maps with Adaptive nonlinear Hebbian learning algorithm*, Int. Math., **15** (2017), 1556–5068.

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