Backpropagation in Fuzzy Cognitive Map Model applied on classification problems

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1 Introduction

Fuzzy Cognitive Maps (FCMs) are a modeling methodology that combines graph theory, fuzzy logic, and neural networks (NN) to represent and analyze complex systems through directed graphs, where nodes represent concepts and edges represent causal relationships with weights in the range [-1,1]. Introduced by Bart Kosko in 1986, FCMs allow for the modeling of positive or inverse influences between concepts, facilitating the understanding of complex systems [6].

This abstract paper summarizes the first author's Bachelor Thesis, where we focus on the development of a single-label classifier using an FCM model. It enables the creation and application of classical FCMs while integrating recent theoretical advancements, including boundary state space estimation [3] and methodologies for computing relative activation values (RAVs) [2]. Also, this results were presented in the Informatics International Conference in Havana [12].

2 Methodology

A review of the existing literature reveals tools developed for creating and experimenting with FCMs [4, 7–9, 11, 13]. They are limited compared to the growing number of publications on FCMs in recent years. Many of these tools are domain-specific or lack advanced model parameter adjustment options, restricting adaptability to various contexts. Additionally, several implementations are outdated and do not incorporate recent theoretical advancements, using fuzzy logic rather than modern machine learning methods. While some implementations are developed in Java for robustness and efficiency, the majority of Machine Learning libraries are in Python, creating challenges in integrating FCM models within Machine Learning environments.

The training of NN adjusts their internal parameters to perform complex tasks and derive rules from data, enabling generalization to new situations and optimizing resource use. While Backpropagation is a key algorithm in Machine Learning, FCMs typically employ other optimization methods like Hebbian or population-based algorithms. However, this research applies Backpropagation to train a time-unfolded FCM model. It's a relatively novel approach because few studies focus on applying Backpropagation to pure FCMs without combining them with black-box models. Additionally, Backpropagation was chosen over classical methods for its efficiency in handling multiple concepts, avoiding the computational costs of tracking weight matrices in other methods.

Backpropagation requires a differentiable loss function for optimization. We introduce a flexible approach, combining convergence and accuracy losses. The convergence loss prevents the model from settling into unstable states, ensuring reliability, while the accuracy loss enhances task precision (e.g., classification). The loss function measures prediction error between the expected value and network output passed through RAV defined in [2], with various options like mean squared error or log-loss. Cross-entropy was used in experiments, as it penalizes incorrect predictions and aligns with information theory.

The classifier topology follows the method in [2], using a *class-per-output* architecture. Each feature connects to an input neuron, while categories link to output neurons. Causal connections exist between input and output neurons, excluding self-connections. In addiction, we use Quasi-nonlinear inference [10], which includes a non-linearity coefficient $\phi \in [0, 1]$ to control the influence of the activation function on the neuron's initial activation. The authors showed that for $0 \leq \phi < 1$, fixed points are not unique, and cycles may appear in special cases.

The experiments used 34 public datasets from KEEL [1] and UCI [5] repositories. Data was normalized to $[0, 1]$ and split 80% for training and 20% for testing, maintaining class proportions. Ten FCMs were built per dataset, with learning using a ϕ parameter in $[0.4, 0.6]$. So, maximum test accuracy values were compared with the results in the article *On the Universal Approximation Property of FCMs* [2], where RAV is formally introduced for the first time and the author uses RAV for training the classifier with Particle Swarm Optimization(PSO). The developed model achieves an average accuracy of 82%, while the PSO-trained model only reaches an average accuracy of 75%.

3 Concluding Remarks

A Python package based on the basic FCM model was developed for easy customization in research. It includes state-space results for predicting FCM dynamics, helping experts make better decisions on model weights and parameters. The package uses TensorFlow for its robust framework, supporting differentiable programming to improve code reusability and maintenance.

A new classification protocol, using RAVs, enables the FCM to act as a single-label classifier. A novel loss function was introduced during training to penalize errors and encourage FCM convergence. This, along with Backpropagation and the quasi-nonlinear inference rule to avoid fixed points, increases the model's reliability and effectiveness.

When compared to the FCM-RAV(PSO) classifier, this new model shows a 7% improvement in maximum average accuracy. Despite being a basic classifier without hidden layers, it achieves an average accuracy of 82% and performs well in binary classification, encouraging further research for better prediction rates.

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