Evolving Hyperboxes for Enhanced Classification and Scalable Feature Selection

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Abstract

When humans observe objects that are not familiar to them, such as a set of unknown characters or images, they tend to group them by their similarity, shape or size and form the abstract view of those specific things for further decision-making. This way describes human cognition involving several levels of granularity (i.e., abstraction) to understand the real world and ensuing cognitive process more effective. We highlight the importance of granules as hyperboxes for classification tasks and feature selection due to their simplicity, effectiveness, and robustness.

Our research aims to utilize a granular computing concept as hyperboxes to construct a hybrid model to enhance the classification performance and scaling feature selection process.

Keywords: Data mining, Feature Selection, Fuzzy Set, Fuzzy Rough Set

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1 Introduction

In 1965, Zadeh [23] introduced the new concept called Fuzzy Sets to manipulate the imprecise data into the fuzzy pattern. Fuzzy logic aims at creating approximate human reasoning that is helpful for cognitive decision making. A hybrid system like the artificial neural network with fuzzy logic has proven its effectiveness in real-world problems [8]. The main advantage of artificial neural systems is their adaptability, making models good at understanding patterns but not enough to explain how to reach their soft decisions.

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In 1992, Simpson [21] proposed a supervised single-pass dynamic neural network classifier known as Fuzzy Min-Max Neural Network (FMNN) to deal with pattern classification using fuzzy sets as pattern classes. FMNN employs n-dimensional hyperbox fuzzy sets to represent pattern spaces, i.e., the union of fuzzy hyperboxes form an individual pattern class.

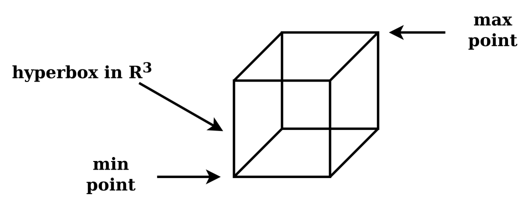

Figure 1. Min-max hyperbox in 3-D

A hyperbox is represented as a region in n-dimensional pattern space characterized by minimum point, maximum point and fuzzy membership function [21]. The hyperbox having min and max points in 3-dimensional space is depicted in Fig. 1. A fuzzy membership function of hyperbox describes the degree of pattern fits within the restricted region. The maximum size of hyperbox is controlled by ($0 \leq \theta \leq 1$), user-defined parameter. FMNN training involves three stages for acquiring knowledge: *Hyperbox Expansion process, Overlap test and Contraction process.*

- Expansion: Identify the hyperbox that can expand and expand it. If an expandable hyperbox cannot be found, add a new hyperbox for that class.
- Overlap Test: Determine if any overlap exists between hyperboxes from different classes.
- Contraction: If overlap between hyperboxes that represent different classes does exist, eliminate the overlap by minimally adjusting each of hyperboxes.

FMNN learning is established by adjusting the min-max points of hyperboxes to acquire knowledge in the pattern space which is helpful for pattern classification [21]. FMNN has several salient properties as a classification model: Online adaptation, Non-linear separability, Overlapping classes, fast training time, hard and soft decision. The main advantage of FMNN is that it has the potential to learn approximate decision concepts through single pass training. FMNN has been applied successfully in different applications such as fault

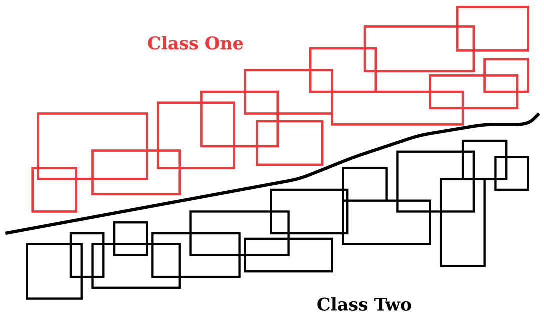

Figure 2. An example of FMNN hyperboxes aloing the boundary of a two-class

detection, lung cancer, medical data analysis, classification of music and text classification etc [1, 2, 5, 16–20, 25].

The knowledge of hyperboxes provides a granular representation of pattern space. This research investigates the ways for building hybrid soft computing models for building classifiers and scalable feature selection.

2 Research Motivation

2.1 Enhanced classification

kNN classification algorithm doesn't have any training phase and performs an expensive testing phase. Each test pattern has to be evaluated with all the training patterns.

Even traditional FMNN is a robust and powerful learning model; still, this model faces problems due to the problem with the contraction process, which may lead to increased misclassification. Contraction steps in FMNN lead to tampering of the non-ambiguous region (overlapping region) by modifying min-max points between hyperboxes in overlapped classes, which create classification errors. Several published FMNN variants include various improvements and enhancements on original FMNN to increase classification performance; they still exhibit certain limitations that affect FMNN classification performance.

Hence, our research focuses on combining simple structure of FMNN (without contraction steps) with kNN strategy such that the combined hybrid model overcomes the limitation of each of the individual models.

2.2 Scalable feature selection

Fuzzy rough set (FRS) theory [6, 7] is a hybridization of rough sets[14] and fuzzy sets [23]. Fuzzy rough feature selection provides a means to deal with both discrete or real-valued noisy data without the need for prior and domain-specific knowledge about data. There are two important procedures to obtaining fuzzy rough feature selection: fuzzy degree of dependency and fuzzy discernibility matrix (FDM). In current objectives or researches, our approaches are proposed based on fuzzy discernibility matrix. A discernibility matrix (M) of decision system is a symmetric $|U| \times |U|$ matrix. Each entry contains a set of attributes and their memberships.

The existing FRS approaches involve object-based computations for feature selection. These approaches require the generation of fuzzy similarity matrices having a memory requirement of $O(|U|^2|C|)$ beforehand where $|U|$ is the size of the object space and $|C|$ is the size of the attribute space. Therefore, an increase in object space will have adverse impacts upon computational overhead in such approaches.

Hence, our research focuses on reducing the space complexity for enhancing the scalability of FRS model using FMNN preprocessing.

3 Research Contribution

A brief summary of each contribution of the research is given below:

3.1 Hybridization of Fuzzy Min-Max Neural Networks with kNN for Enhanced Pattern Classification

FMNN is a single epoch learning Pattern classification algorithm with several advantages for online learning. The improved FMNN variants have been obtained at increased cost of training as additional is added to the simple three-layer architecture of FMNN [4, 12, 13, 15]. We propose the methodology (kNN-FMNN) for achieving the better classification accuracies without resorting to modification of the structure of FMNN. This work proposes a hybridization of FMNN with kNN algorithm for achieving the ability to handle decision making in overlapped regions without altering the structure of FMNN.

FMNN gives a natural way to group the nearest objects into granular structure of hyperbox. So using this we can restrict the space in which k nearest neighbour computation needs to be performed. This aspect we are employing in dealing w.r.t. overlapping region of FMNN testing algorithm.

Comparative studies with existing approaches over benchmark decision systems have proved the utility of the proposed kNN-FMNN approach.

The work in this contribution has been published in [11]

3.2 Scalable Fuzzy Rough Set Reduct Computation Using Fuzzy Min–Max Neural Network Preprocessing

FRS is a hybridization of rough sets and fuzzy sets and provides a framework for feature selection. However, the existing FRS-based feature selection approaches are intractable for large datasets due to the space complexity $O(|U|^2|C|)$ of the FRS methodology [3, 22, 24]. We propose a novel FDM-FRS feature selection approach utilizing the FMNN as a preprocessing step that can enhance the scalability of FRS approaches. our main contribution is as follows:

- FMNN model is used to reconstruct the object-based decision system into a hyperbox-based interval-valued decision system.
- Then, a novel way of constructing the fuzzy discernibility matrix from the interval-valued decision system is introduced.
- Sequential forward selection based feature selection measure is applied on the induced fuzzy discernibility matrix to find feature selection.

Comparative experimental analysis has been done with the existing FRS approaches on benchmark datasets and established the relevance of the proposed approach. The proposed approach obtained the exact features in most of the datasets in much lesser computational time than existing FRS approaches while preserving similar classification accuracy. Also, our method achieved enhanced scalability to such large decision systems, at which it is not possible to obtain features by existing FRS approaches.

Here, the whole motivation behind this contribution is to use an interval-valued decision system instead object space decision system in fuzzy discernibility matrix construction for feature selection that can significantly decrease computational time and memory utilization.

The work in this contribution has been published in [9]. Also, an incremental version of this contribution has been published in [10].

4 Conclusion and Future Work

In this research work, we explored the hybridization of FMNN with kNN to overcome the contraction step in FMNN and enhance pattern classification. Also, we studied the hybridization of FMNN with FRS model for scalable feature selection in the decision system. The objective of FMNN preprocessing on FRS model for feature selection in the proposed FDM-FMFRS is achieved in the enhanced scalability on benchmark datasets. The proposed approach could scale to feature computation in such large datasets, over which existing FRS approaches cannot arrive due to space constraints. In the future, we will improve further scalability our research work using distributed and parallel approaches.

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