

# Chapter 4

## A New Efficient and Effective Fuzzy Modeling Method for Binary Classification

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### ABSTRACT

*This paper presents a new fuzzy modeling method that can be classified as a grid partitioning method, in which the domain space is partitioned by the fuzzy equalization method one dimension at a time, followed by the computation of rule weights according to the max-min composition. Five datasets were selected for testing. Among them, three datasets are high-dimensional; for these datasets only selected features are used to control the model size. An enumerative method is used to determine the best combination of fuzzy terms for each variable. The performance of each fuzzy model is evaluated in terms of average test error, average false positive, average false negative, training error, and CPU time taken to build model. The results indicate that this method is best, because it produces the lowest average test errors and take less time to build fuzzy models. The average test errors vary greatly with model sizes. Generally large models produce lower test errors than small models regardless of the fuzzy modeling method used. However, the relationship is not monotonic. Therefore, effort must be made to determine which model is the best for a given dataset and a chosen fuzzy modeling method.*

### INTRODUCTION

Binary classification refers to the task of classifying an unknown object into one of the two known classes. Many real world problems can be formulated as binary classification problems. The examples are numerous, which include determining whether a patient has certain disease or

not, determining whether an artifact is defective or not, determining whether an email is a spam or not, and so on.

Before classification can be carried out, a classification system or a classifier must be built first. A classification system or classifier built for performing binary classification is called a binary classifier. Many machine learning methods

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such as decision trees, neural networks, support vector machines, and fuzzy models are suitable for building binary classifiers. Of interest in this paper are fuzzy models.

A fuzzy model is comprised of a set of fuzzy if-then rules. Various forms of fuzzy rules are possible. Most well-known among them are Mamdani linguistic rules and TSK rules, as described below for an  $n$ -input and single-output system.

- **Mamdani linguistic rules** are of the form of  $R_i$ : If  $X_1$  is  $A_{1i}$  and  $X_2$  is  $A_{2i}$ , ..., and  $X_n$  is  $A_{ni}$ , then  $Y$  is  $B_i$ . In each Mamdani rule,  $X_n$  denotes the  $n$ th input variable,  $A_{ni}$  the fuzzy set associated with  $A_n$ , and  $B_i$  the fuzzy set associated with output variable  $Y$  of rule  $R_i$ .  $B_i$  can be represented by its modal value or as a fuzzy singleton for fuzzy control and classification applications.
- **TSK rules** are of the form of  $R_i$ : If  $X_1$  is  $A_{1i}$  and  $X_2$  is  $A_{2i}$ , ..., and  $X_n$  is  $A_{ni}$ , then  $Y = b_{0i} + b_{1i}X_1 + b_{2i}X_2 + \dots + b_{ni}X_n$ . In each TSK rule,  $X_n$  denotes the  $n$ th input variable,  $A_{ni}$  the fuzzy set associated with  $A_n$ , and  $b_i$  is a parameter vector and  $b_{0i}$  is a scalar offset associated with rule  $R_i$ . If all parameters in the vector  $b_i$  are zeros, then TSK rules are identical to Mamdani rules with  $B_i$  being fuzzy singletons.

A fuzzy model built for classification consists of a set of fuzzy classification rules of the following form  $R_i$ : If  $X_1$  is  $A_{1i}$  and  $X_2$  is  $A_{2i}$ , ..., and  $X_n$  is  $A_{ni}$ , then  $Y$  is  $B_i$ . In each classification rule,  $X_n$  denotes the  $n$ th input variable,  $A_{ni}$  the fuzzy set associated with  $A_n$ , and  $B_i \in \{B_1, B_2, \dots, B_m\}$  representing the class label of rule  $R_i$ . For binary classification problems, there are only two values, i.e.,  $B_i \in \{B_1, B_2\}$ . Fuzzy classification rules are identical to Mamdani rules with  $B_i$  being fuzzy singletons or TSK rules with  $b_i$  being zeros. Each rule could be assigned a rule weight. If not explicitly assigned, each rule is considered having rule weight of one.

Fuzzy models can be built manually or interactively using a tool designed to do that, e.g. the FIS Editor in the Matlab fuzzy toolbox. These approaches, however, require *a priori* knowledge about the model. The alternative is to build fuzzy models from data for which numerous methods have been proposed. These data-driven methods can be grouped into the following categories (Liao, 2006):

- **Grid partitioning:** This method divides the domain space into overlapped rectangular parallelepiped grids by specifying the number and shape of membership functions along each dimension. Data is then used to choose rule consequent and to compute rule weight. The earliest and most famous paper in this category is the method proposed by Wang and Mendel (1992), called the WM method later.
- **Fuzzy clustering:** This method applies a fuzzy clustering algorithm to partition the domain space, either one dimension at a time or all dimensions together at one time. The former approach works like grid partitioning except that the data distribution is taken into account. The fuzzy c-means variant-based method is an example (Liao, 2004). The latter approach generates a set of rules with each corresponding to a cluster. The membership function along each dimension could be obtained by projection, but might not be interpretable. The *genfis2* function in the Matlab toolbox is an example, which implements the fuzzy subtractive clustering method.
- **Genetic-fuzzy modeling or using other metaheuristics:** This method involves the use of a genetic algorithm to help determine model structure and/or model parameters. Interested readers are referred to Cordon et al. (2004) for an overview of genetic fuzzy systems. The uses of other

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