Real Life Applications of Fuzzy Decision Tree

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ABSTRACT
Fuzzy Decision Tree is becoming increasingly significant as it is applied to areas of different platforms in real life. This paper gives an overview of the applications of fuzzy decision tree in heterogeneous fields. It is being actively used in fields as varied as intrusion detection, flexible querying (modus ponens), analysis of cognitive process (Human Computer Interaction), for user authentication in biometrics, as parallel processing support, in stock-market, for information retrieval and data mining. The fuzzy logic approach allows the direct incorporation of expertise. Moreover, it is shown that the decision taken by means of a fuzzy decision tree is more stable when observation evolves. The powerful combinatorial methods found in fuzzy logic have been used to prove fundamental results in other areas namely medical, educational, chemical and multimedia.

Keywords
Biometric, Classification, Data mining, Fuzzy decision tree, Fuzzy logic, Intrusion Detection, parallel processing, TAFPA, HCI

1. INTRODUCTION
Recent times have seen an explosive growth in the availability of various kinds of data. It has resulted in unprecedented opportunity to develop automated data-driven techniques of extracting useful knowledge. A decision tree [1,2] is a hierarchical set of rules that recursively partitions a data space occupied by a set of training samples. In the simplest case, each rule can be thought of as a boundary that partitions the data space along one variable into two disjoint subspaces and directs new samples to one of the resulting subspaces. It is a tree in which each branch node represents a choice between a number of alternatives, and each leaf node represents a decision. The decision tree method is useful because it produces an interpretable classification model even for high-dimensional data.

Unfortunately, owing to the nature of the split selection process, there is uncertainty related to the location of a decision boundary. Fuzzy partitions can be used to account for the uncertainty in decision boundary location. A fuzzy decision tree is defined as a decision tree that uses fuzzy partitioning. Fuzzy decision trees come in two general varieties: (1) those that are concerned with propagating noise estimates in the measurement variables [3] and (2) those that blur crisp decision boundaries to account for sample proximity [2,4]. This paper concentrates on the latter variety.

In this paper, we present a few selected real life applications of Fuzzy Decision Tree to data mining, stock markets, information retrieval, biometrics, Human computer interaction, intrusion detection, cognitive process and parallel processing support.

2. FUZZY LOGIC AND FUZZY DECISION TREE
In many real world applications the data used are inherently of imprecise and subjective nature. When an expert tries to analyze a certain event, fact or what ever in a real world environment, she or he usually expresses the estimates with some degree of confidence and operates with the terms like ”highly favorable”, “rather favorable”, “absolutely inauspicious” and so on. These estimates can be represented as numerical or logical values. The use of numerical values makes the search of common characteristics from the input attributes more difficult because of variety of real values. The use of Boolean or Multi-Valued logic approaches does not always give necessary reliance. There is another significant drawback of such crisp approach to data evaluation: in many cases it is against the nature of human beings. People use their subjective feelings, background knowledge and short-time memory, rather than any frequency criteria, to distinguish different data.

Fuzzy logic is a popular approach to capture this vagueness of information [5]. The basic idea is to come from the “crisp” 1 and 0 values to a degree of truth or confidence in the interval [0,1]. Fuzzy set theory was first proposed by Zadeh[6] to represent and manipulate data and information that possess non-statistical uncertainty. Fuzzy set theory is primarily concerned with quantifying and reasoning using natural language in which words can have ambiguous meanings. This can be thought of as an extension of traditional crisp sets, in which each element must either be in or not in a set. Fuzzy sets are defined on a non-fuzzy universe of discourse, which is an ordinary sets. A fuzzy sets F of a universe of discourse U is characterized by a membership function $\mu_F(x)$ which assigns to every element x∈U ,a membership degree $\mu_F(x) \in [0,1]$. An element x∈U is said to be in a fuzzy sets F if and only if $\mu_A(x) > 0$ and to be a full member if and only if $\mu_F(x) = 1$ [7]. Membership functions can either be chosen by the user arbitrarily, based on the user’s experience, or they can be designed by using optimization procedures[8][9]. Typically, a fuzzy subset can be represented as,

$$A = \left\{\frac{\mu A(x1)}{x1}\right\}, \left\{\frac{\mu A(x2)}{x2}\right\}, \ldots\ldots\ldots\ldots \left\{\frac{\mu A(xn)}{xn}\right\}$$

where the separating symbol / is used to associate the membership value with its coordinate on the horizontal axis.

Fuzzy decision trees (FDTs) are a generalization of decision trees to handle attributes with numeric-symbolic values, i.e. attributes associated either with a numerical value (for instance, the size is 172 cm) or a symbolic value corresponding to a numerical measure (for instance, the size is big). FDT is a very promising learning tool because it represents induced knowledge in a very expressive way. The knowledge represented as a FDT is understandable and it differs from black box systems as neural networks. Moreover, a FDT is equivalent to a set of fuzzy rules [10], and such kind of induced rules can be introduced to optimize the query process of the database [11,12] or to deduce decisions from data. FDTs enable us to obtain various kinds of such rules. Thus, it is a powerful knowledge representation. A FDT, as a set of fuzzy rules, can be used as knowledge base to apply in real life.

3. APPLICATIONS

3.1 Intrusion Detection

Developing effective methods for the detection of intrusions and misuses is essential for assuring system security. Various approaches to intrusion detection are currently being in use with each one has its own merits and demerits. The objective of this study is to test and improve the performance of a new class of decision tree as explained in [13] based IDS.

The C-fuzzy decision trees are classification constructs that are built on a basis of information granules fuzzy clusters. The way in which these trees are constructed deals with successive refinements of the clusters (granules) forming the nodes of the tree. When growing the tree, the nodes (clusters) are split into granules of lower diversity (higher homogeneity). The performance, robustness, and usefulness of classification algorithms are improved when relatively few features are involved in the classification. Thus, selecting relevant features for the construction of classifiers has received a great deal of attention. Several approaches to feature selection have been explored [14]. The purpose is to identify best candidate feature subset in building the c-fuzzy decision tree [15] IDS that is computationally efficient and effective. The usefulness of c-fuzzy decision tree for developing IDS with a data partition is based on horizontal fragmentation. The focus is on improving the performance by reducing the number of features and selecting more appropriate data set. It is evident from the results, our data partition and feature selection technique results in improved c-fuzzy decision tree to build an effective IDS.

3.2 Flexible Querying

Nowadays, a large amount of data is contained in a lot of databases. These data represent an important source of potential knowledge to use. Data mining is the process of mining databases in order to induce such knowledge [16]. Fuzzy data mining is concerned by the mining of fuzzy knowledge [17]. For instance, the FDT construction method can be applied to mine a database and extract fuzzy knowledge. The fuzzy rule base induced as a FDT is a new form of knowledge that can be associated with the database. This knowledge can be used in different ways.

First of all, it enables us to improve the querying process of the database. A set of rules can be introduced to optimize the query process of the database [19] or to deduce decisions from data. Such a set of induced fuzzy rules can be associated with a database as a knowledge base that can be used to help answering frequent queries. A fast response can be found for a query on the value of an attribute. It can also lower the conditions on the values of attributes for a query, before the process of examination of the database. Moreover, fuzzy rules can take advantage of the fuzziness of their values to take into account new numerical or fuzzy values. The method of classification with such a set of fuzzy rules is a good way to handle new values for attributes. Secondly, a set of fuzzy rules is completely understandable and a decision taken by means of these rules is explainable. It can be used as a new knowledge on the domain of the database, and it can be understood by any expert of this domain. The method of classification by means of a fuzzy decision tree [20] lies on the use of measure of satisfiability to compare observed values to testing values. It has been proved that such a method ensures the cognitive process used in this kind of reasoning. Moreover, by using a fuzzy decision tree instead of a classical decision tree, a slight change in the values of a description leads to a slight change in the value of the decision.

Given a measure of satisfiability and a process of inference by means of a fuzzy decision tree, we showed that a continuity in the value of the decision is obtained relatively to the values of the description. Thus, the stability of fuzzy decision trees when classifying evoluting observations results from this continuity.

3.3 User Modeling from Human-Computer Interaction

A fundamental objective of human-computer interaction research is to make systems more usable, more useful, and to provide users with experiences fitting their specific background knowledge and objectives. The challenge in an information-rich world is not only to make information available to people at any time, at any place, and in any form, but specifically to say the “right” thing at the “right” time in the “right” way. Providing helpful analysis of cognitive process is one of the main concerns for user modeling and adaptive hypermedia conception. TAFPA (Tree Analysis For Providing Advices)[21] system uses a learning agent, a fuzzy decision tree, which works on traces of human-computer interactions by providing advices that come from people who have the same cognitive behavior. The TAFPA software is based on the first kind as an analysis of the cognitive activity of a user is completed to provide hints. Domain-oriented design environments allow computers to be invisible thus enabling designers to communicate with domain-specific concepts, representations, and tools. By bringing objects closer to the conceptual world of their users, the domain orientation of these environments makes HCI(Human Computer Interaction) more usable, more useful, and more learnable. Domain-oriented design environments integrate a number of components relevant to user modeling. These hints are related to the design of the environment and provide the user tips to use helpful functions of the interface.
TAFPA is thus provided with a learning agent that is trained and that is used to give advices to make easier the use of the given software. In a first phase, the training phase, the learning agent is trained by using a set of interactions that have been stored when well-known computer-skilled users have interacted with the given environment. Thus, this agent learns the cognitive characteristics that these user interactions could give. Afterwards, during the operational phase, TAFPA handles the interactions of a user with the environment and uses the learned agent to classify the user as experimented or

not. If necessary an advice could be suggested by TAFPA to the user to solve better the task he is faced with.

This methodology can be applied to Adaptive Hypermedia Educational Systems. It is domain independent and can be used for providing help to teachers as it builds a cognitive model of the student.

3.4 User Authentication in Biometrics

Biometric based personal authentication can be viewed as procedural technique where the claimed identity is authenticated based on user's physiological/behavioral traits. The principal steps in authentication system generally include: the acquisition of the biometric trait, feature extraction, generation of matching scores, and calculation of error rates, i.e. false acceptance rate (FAR) and False Rejection Rate (FRR) by comparing these scores against different thresholds [22]. The complete security and authentication is dependent on this threshold and hence its appropriate selection is central to any biometrics based security system. A conventional way to choose the best threshold in a system is to plot the two associated error rates (FAR/FRR) on a ROC curve and select the suitable threshold according to the tradeoff between the error rates . One of the main requirements of the biometric security systems are that it should operate on low error rates, especially FAR, i.e., accepting imposters as genuine users. Depending upon application, the weight of FAR(False Acceptance Rate) or FRR(False Rejection Rate) may be different. For example, a personal authentication system generally requires a FAR less than 0.01%. To design a classification system which can achieve such accuracy, two very important considerations are: (1) The choice of a suitable classifier with relevant classification technique (2) The choice of biometric features which are used for training the classifier. The neural network based classifier has been the most frequently used classification system utilized by several authentication systems. However, it generally works on high computational complexity and hence sometimes inapplicable for online security systems.

The usage of FSLIQ and FDT is investigated for the biometric authentication by considering the two class classification approach. The basic ID3 (Iterative Dichotomiser 3) [23] is used to generate decision tree which is further pruned to get the final trained tree. For each class, an appropriate membership function is defined based on the training data belonging to the class. Each data has a fuzzy representation according to the membership function and it can belong to a particular class based on this representation. To find the divider nodes of the tree two algorithms: fuzzy entropy and gini index is used which is calculated for each data and the node is selected based on highest entropy/index. The final decision about the classification is made through a threshold based on pruning[24] of the tree. The matching scores generated from training set is used to train the FDT and the algorithm is tested by generating same set of scores from testing set. The Testing accuracy obtained by applying FSLIQ on iris taken from UCI Machine Learning Repository(http://archive.ics.uci.edu/ml/datasets.html) is 98% as shown in Table1.

The advantage of the FDT based approach is that the rules generated in this approach can be further modified by users, which makes it more flexible for real time application; especially for biometric authentication where security requirements changes according to the applications. Thus, the prime focus of this research is to make a real time biometric authentication security system using fuzzy decision tree supported classifier.

3.5 Parallel Processing Support

Decision tree induction[25] has been widely used in extracting knowledge from feature based examples for classification and decision-making. Decision tree induction algorithms function recursively. First, an attribute must be selected as the root node. In order to create the most efficient (i.e, smallest) tree, the root node must effectively split the data. Each split attempts to pare down a set of instances (the actual data) until they all have the same classification. The best split is the one that provides what is termed the most information gain. An induction algorithm is used to learn a classifier, which maps the space of feature values into the set of class values. Detecting every feature value can be obtained by diagnostic tests of input attributes that have associated with integrated (financial and temporal) costs. Objective is to minimize the cost of diagnostics. Decision tree approach applicable to parallel processing[26] search for an optimal (or sub-optimal) sequence of tests to be undertaken when recognize a new subject to fulfill the objective.

Fuzzy defined data are more accurate in reflecting a real around world. It is able to analyze the order in which different diagnostic tests should be performed in order to minimize the diagnostics costs and to guarantee a desired level of accuracy. For this purpose, a technique to compute cumulative information estimations of fuzzy sets is used. The use of cumulative information estimations allows precisely estimating mutual influence of attributes. The application of such estimations allows inducing minimum cost decision trees based on new optimality criteria. For this, a new type of fuzzy decision tree: ordered tree. Ordered tree differs from unordered fuzzy decision tree in the way of testing attributes. In ordered trees the order of attribute tests is independent from the results of previous tests, so we can test next attributes in parallel. This leads to decreasing of expenditures for test attributes. These evaluations are tool for analysis of training and estimations are based on Shannon's entropy analogue. The use of such estimates allows inducing minimum cost decision trees based on different criteria. Parallel processes were used for resolving time-consuming tasks in many scientific problems. The problem of parallelizing the process of building a fuzzy decision tree can be treated stage by stage. At the first step a fuzzification of the continuous data can be parallelized. If for each interval is created one process, than the level of parallelism will be equal to the number of intervals. The second improvement is possible through searching for maximum of the increment of information about the attribute at minimum cost, which can be done in parallel. Using parallel processes can also decrease the time for mining of association rules and programming model of the processes must be carefully selected to reflect their real configuration.

3.6 In Stock-Markets

Time series data are of growing importance in many new database applications, such as data mining. A time series is a sequence of real numbers, each number representing a value at a time point. For example, the sequence could represent stock or commodity prices, sales, exchange rates, weather data biomedical measurements, etc. For example, we may want to find stocks that behave in approximately the same way (or approximately the opposite way) for hedging; or products that had similar selling patterns during the last year; or years when the temperature patterns in two regions of the world were similar. In queries of this type, approximate, rather than exact, matching is required. Most of the existing data mining techniques are not so efficient to dynamic time series databases. However mining different queries from huge time-series data is one of the important issues for researchers.

New Fuzzy Decision Tree (FDT)[27] for unpredictable dynamic stock exchange databases has been constructed by using weighted fuzzy production rules (WFPR). In WFPR, assign a weight parameter to each proposition in the antecedent of a fuzzy production rule (FPR) and assign certainty factor (CF) to each rule. It is based on minimum classification information entropy to select expanded attributes. In similarity-based fuzzy reasoning method we analyze WFPR's which are extracted from FDT. The analysis is based on the result of consequent drawn for different given facts (e.g. variables that can affect stock market) of the antecedent. Certainty factors have been calculated by using some important variables (e.g. effect of other companies, effect of other stock exchanges, effect of overall world situation, effect of political situation etc) in dynamic stock market. Some advantages such as accurate stock prediction, efficiency and comprehensibility of the generated WFPR's rules, which are important to data mining. These WFPR's allow us effectively classify patterns of non-axis parallel decision boundaries using membership functions properly, which is difficult to do using attribute-based classification methods.

3.7 Information Retrieval and Data Mining

Information retrieval and data mining are two components of a same problem, the search of information and knowledge extraction from large amounts of data, very large databases or data warehouses.

In information retrieval, the user knows approximately what he looks for, for instance an answer to a question, or documents corresponding to a given requirement in a database. The search is performed in text, multimedia documents (images, videos, sound) or in web pages. The main difficulty lies in the identification of relevant information, i.e. the closest or the most similar to the user's need or expectation. The most ideal property of any query processing system for efficient information retrieval is the ability to handle regular queries in the form of either quantitative or qualitative queries and fuzzy queries that are expressed with ambiguous or fuzzy terms. Fuzzy query processor applies the concept of fuzzy logic to handle ambiguous terms used in query expressions. To make the query processor correctly respond to queries, fuzzy logic is applied. Asking the user to elicit what he looks for is not an easy task and, the more flexible the query-answer process, the more efficient the retrieval. With the help of fuzzy sets in knowledge representation enables the user to express his expectations in a language not far from natural. Approximate matching between the user's query and existing elements in the database, lies on the basis of similarities and degrees of satisfiability.

In data mining, the user looks for new knowledge, such as relations between variables or general rules for instance. The search is performed in databases or data warehouses. The purpose is to find homogeneous categories, prototypical behaviors, general associations, important features for the recognition of a class of data. Most conventional data-mining algorithms identify the relationships among transactions using binary values and find rules at a single concept level. Transactions with quantitative values and items with hierarchy relation are, commonly seen in real-world applications. In this case again, using fuzzy sets brings flexibility in knowledge representation, interpretability in the obtained results, in rules or in characterizations of prototypes. Looking for too strict a relation between variables may be impossible because of the variability of descriptions in the database, while looking for an imprecise relation between variables or to a crisp relation between approximate values of variables may lead to a solution. The expressiveness of fuzzy rules or fuzzy values of attributes in a simplified natural language is a major quality for the interaction with the final user.

The main problems in information retrieval and data mining lie in the large scale of databases, especially when dealing with video or web resources, in the heterogeneous data of various types, numerical or symbolic, precise or imprecise, ambiguous, approximate, with incomplete files, uncertain because of the poor reliability of sources or the difficulties of measurement of observation. Fuzzy logic is very useful in this matter because of its capability to represent miscellaneous data in a synthetic way, its robustness with regard to changes of the parameters of the user's environment, and its unique expressiveness.

Based on the similarity framework and the fuzzy learning methods both belong to the data mining and information retrieval fields, and cover several domains, namely medical, educational, chemical and multimedia. Compared to conventional crisp-set-mining methods for quantitative data, fuzzy approach gets smoother mining results due to its fuzzy membership characteristics. For each application, the objective of the task, the considered data, the applied method and the obtained results are successively described[26].

4. Experimental Results

FDT based approach using SLIQ and FSLIQ is applied on UCI data sets taken from UCI Machine Learning Repository to calculate the Testing accuracy.

Table1. Classification Accuracy and Elapsed Time on UCI

UCI Dataset	Testing Accuracy using SLIQ	Testing Accuracy using Fuzzy SLIQ
Haberman	65.81	73.23
Iris	98	98
Liver	57.14	61.43
Diabetes	67.92	72.21
Wisconsin BC	93.33	95.65
Echocardiogram	84	82.00
Wine	88.33	88.89
Heart Stat Log	74.33	76.33

5. CONCLUSION

Real world applications address a double challenge. On the one hand they are responses to specific problems with their specific constraints and on the other hand they have to build on solid and general theoretical foundations. Moreover, we proved that using a fuzzy decision tree instead of a classical decision tree, a slight change in the values of a description leads to a slight change in the value of the decision. Given a measure of satisfiability and a process of inference by means of a fuzzy decision tree, we showed that a continuity in the value of the decision is obtained relatively to the values of the description. Thus, the stability of fuzzy decision trees when classifying evoluting observations results from this continuity. Comparing SLIQ and Fuzzy SLIQ algorithms in Table1 clearly shows the difference in Testing accuracy, when Fuzzy concept is added to SLIQ. We obtain 98% accuracy (i.e. best) on iris from UCI repository. Also, very less time is consumed.

Finally, what makes all these applications unique is the use of fuzzy logic. In fact, their success is due, to some extent, to its capability to represent diverse types of data in a synthetic way, its robustness with regard to changes or noise, and obviously its unique expressiveness, crucial for the understanding of the results.

6. REFERENCES

[1] Breiman L, Friedman JH, Olshen RA, Stone CJ. Classification and Regression Trees. Wadsworth: Belmont, CA, 1984.

[2] Quinlan JR. C4.5 Programs for Machine Learning. Morgan Kaufmann: San Mateo, CA, 1993.

[3] Yuan Y, Shaw MJ. Induction of fuzzy decision trees. Fuzzy Sets Syst. 1995; 69: 125–139.

[4] Suarez A, Lutsko JF. Globally optimal fuzzy decision trees for classification and regression. IEEE Trans. Pattern Anal. Machine Intell. 1999; 21: 1297–1311.

[5] Zadeh L.: Fuzzy sets, Information and control, 8, pp.407–428, 1965.

[6] L. A. Zadeh, "Fuzzy sets," Inform. Control, 338-353, 1965.

[7] H. J. Zimmermann, Fuzzy Set Theory and Its Applications, Kluwer Academic Publishers, 1991.

[8] Jang, J.S. R., Self-Learning Fuzzy Controllers Based on Temporal Back-Propagation, IEEE Trans. On Neural Network, Vol. 3, September, 1992, pp. 714-723.

[9] Horikowa, S., T. Furahashi and Y. Uchikawa, On Fuzzy Modeling Using Fuzzy Neural Networks with Back-Propagation Algorithm, IEEE Trans. on Neural Networks, Vol.3, Sept., 1992, pp. 801-806.

[10] B. Bouchon-Meunier and C. Marsala: Learning fuzzy decision rules. Handbook of Fuzzy Sets, Kluwer, Dordrecht 1999.

[11] I-M. A. Chen: Query answering using discovered rules. In: Proc 12th Internat. Conference on Data Engineering, 1996, pp. 402-411.

[12] S. Shekhar, B. Hamidzadeh, A. Kohli, and M. Coyle: Learning transformation rules for semantic query optimization: A data-driven approach. IEEE Trans, on Knowledge and Data Engineering 5 (1993), 6, 950-964.

[13] Witold Pedrycz, Fellow, IEEE, and Zenon A. Sosnowski, “C–Fuzzy Decision Trees”,IEEE Transactions on Systems, Man, and Cybernetics —Part C: Applications and Reviews, VOL. 35, NO. 4,November 2005.

[14] Huan Liu, Lei Yu , “ Toward Integrating Feature selection Algorithms for Classification and Clustering”, IEEE Transaction on Knowledge and data Engineering VOl 17 , No 4, April 2005.

[15] Makkithaya, K., Subba Reddy, N.V., Dinesh Acharya, U."Improved C-Fuzzy Decision Tree for Intrusion Detection", World Academy of Science, Engineering and Technology, vol. 32, 2008.

[16] U. M. Fayyad, G. Piatetsky-Shapiro, and P. Smyth: From data mining to knowledge discovery in databases. AI Magazine 17 (1996), 3, 37-54.

[17] C. Marsala and B. Bouchon-Meunier: An adaptable system to construct fuzzy decision trees. In: Proc. NAFIPS'99 (North American Fuzzy Information Processing Society), New York 1999, pp. 223-227.

[18] I-M. A. Chen: Query answering using discovered rules. In: Proc 12th Internat. Conference on Data Engineering (S.Y.W. Su, ed.),New Orleans 1996, pp. 402-411.

[19] S. Shekhar, B. Hamidzadeh, A. Kohli, and M. Coyle: Learning transformation rules for semantic query optimization: A data-driven approach. IEEE Trans, on Knowledge and Data Engineering 5 (1993), 6, 950-964.

[20] Christophe Marsala. Fuzzy decision trees to help flexible querying. Kybernetika, Vol. 36 (2000), No. 6, 689-705.

[21] Damez, M., Marsala, C., Dang, T., & Bouchon-Meunier, B. (2005). Fuzzy decision tree for user modeling from human–computer interactions. In International conference on human system learning. (pp. 287–302)

[22] Karthik Nandakumar, Integration Of Multiple Cues In Biometric System,M.S. Thesis, http://www.cse.msu.edu/biometrics/Publications/Thesis. 2005

[23] ID3 algorithm.Wikipedia, the free encyclopedia, http://en.wikipedia.org/wiki/ID3algorithm. (May2001)

[24] ID3 algorithm.Wikipedia,the free encyclopedia, http://en.wikipedia.org/wiki/pruning.(May 2011)

[25] Quinlan J.R. : Induction of Decision Trees, Machine Learning, 1, pp. 81-106, 1986.

[26] V.Levashenko, and P.Martincová, "Fuzzy Decision Tree for Parallel Processing Support", Journal of Information, Control and Management Systems, vol.3, 1, 2005, pp. 45-52.

[27] Mohd Noor Md Sap, R. H. Khokhar. Fuzzy Decision Tree for Data Mining of Time Series Stock Market Databases, The fifth International conference for the Critical Assessment of Microarray Data Analysis 2004,USA.

[28] B. Bouchon-Meunier, M. Detyniecki, M.-J. Lesot, C. Marsala, M. Rifqi. "Real world fuzzy logic applications in data mining and information retrieval". Springer, pp. 219-247, 2007.