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FOREWORD

These proceedings contain the papers of the International Conference "Information and Communication Technologies in Business and Education" which took place at the University of Economics – Varna, Bulgaria, 18 October 2019.

The international scientific conference is dedicated to the **50th anniversary of the Department of Informatics at the University of Economics – Varna.** The conference is also dedicated to the 100th anniversary of the University. The included papers describe recent scientific and practical developments in the field of information and communication technologies, information systems, and their applications in business and education.

The papers in the Proceedings are peer reviewed and are checked for plagiarism.

C O N T E N T S

BASIC SOFT COMPUTING METHODS IN USER PROFILE MODELING

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Abstract

User profile modeling is a challenge because of the high degree of subjectivity and uncertainty of human behavior. The traditional methods used to create user profile models do not have the necessary flexibility to capture the inherent uncertainty. The purpose of this research is to present adequate methods for modeling a user profile in their role as a learner. The soft computing methods - neural networks, fuzzy logic, fuzzy clustering, neuro-fuzzy approaches and genetic algorithms – applied individually or in combination with other machine learning methods could be used for this purpose, due to the appropriate specificity of each one of them. The results of a research on the suitability of the basic soft computing methods for modeling a learner's profile are presented in this paper.

Keywords: *Soft computing; User profile modeling; Learner profile model; Student profile model.*

INTRODUCTION

The main challenge in creating a profile model is due to the relevance and precision of the information received from users.The factors that influence the creation of an adequate consumer model are data precision, application of the right methods, the level of data noise and, above all, the degree of subjectivity and uncertainty of human behavior. A user model is created through a user modeling process in which the unobservable user information is derived from the observable information from the same user; for example, using interactions with the system (Zukerman, Albrecht and Nicholson, 2001; Frias-Martinez *et al.*, 2005).

The opportunities for creating user profile models in the current academic work are specifically selected to provide an alternative to creating a personalized student profile model. Further in the current document the term "learner profile model" will be associated with "user profile model". They are classified on the basis of how human behavior is represented as a model and what its purpose is. This largely depends on the type of task the model will be used for. To choose the right model, we stick to the following five types of tasks: (1) *Forecasting*. The ability to anticipate the users need using their past behavior; (2) *Recommendation*. The ability to offer interesting facts to the user based on additional information that is not deduced from their previous behavior (Frias-Martinez *et al.*, 2005); (3) *Classification.* The process of building a model in which data is grouped or classified into one of many predefined classes (Potey and Sinha, 2015); (4) *Clustering.* Adaptation with focus on a group of users. Groups with specific characteristics are identified and clusters are formed on this basis. This is achieved through clustering techniques so as to cluster user models since the group is viewed as a cluster of similar user models. (Nguyen, 2014); (5) *Filtering.* Selection of data that meets user preferences, derived from the whole available user information. Each of the five tasks can be solved using the knowledge contained in the user profile model. For example, consumer data can be *filtered* based on the knowledge of their purposes and interests and *classified* based on predefined classes into stereotypes. Stereotypes can be *grouped into clusters* similar to the model. From the resulting data *a forecast* can be made about the preferences of the user. Finally, *recommendation* can be made that is a result of the knowledge gathered and the information analyzed.

Creating a user profile model can be achieved in two ways: 1) *classic*, where information is provided directly by the user, through a survey, and 2) *automatic*, in which information is collected using an algorithm embedded in the system for creating a user-model which is an implicit process for the user. The second way is a more modern solution and does not involve users answering questions. Machine learning methods can be applied for automatic user profile modeling, using techniques for recognizing patterns in the user behavior, recording them, and integrating them into a profile. The results which the machine learning methods provide are a summary of what has been learned and a description of the knowledge gained. These facts can be used to analyze the original data and make forecasts. From this point of view, data mining and other machine learning methods make it possible to create user profile models automatically. Data Mining (DM) scientists provide an overview of how traditional data mining techniques can be applied for creating a user model (and in particular – a learner's one) and the overall architecture of such systems (Eirinaki and Vazirgiannis, 2003; Atanasova et al., 2019). Romero et al. (2013) propose a model for predicting student achievement using DM techniques such as grouping rules and associative rules. DM is also widely used to model a student profile whose primary purpose is to characterize the student through their emotions, achievements, skills, learning preferences, and the fulfillment of individual educational requirements by adapting the teaching experience to match them better. (Lemmerich, Ifland and Puppe, 2011; Nandeshwar, Menzies and Nelson, 2011). Another area of DM application is student assessment, which allows students' skills to be differentiated at a subtle level (Lopez et al., 2012). This also facilitates student feedback and support (Leong, Lee and Mak, 2012). More generally, DM can be applied for modeling the student profile regarding their emotions in the context, engagement, meta-knowledge, and collaboration tasks (Baker, 2014; Alexandrova and Parusheva, 2017).

However, the traditional methods such as machine learning and DM cannot solve the problem of the uncertainty in the user behavior. Soft computing methods family are designed to overcome this drawback. They are suitable for solving problems and tasks in conditions of inaccurate, unclear or noisy information; information for which accurate data is not available or is based on partial truth (Gupta, Sinha and Zadeh, 2000). The idea of soft computing originates in 1991 when a scientist working in the field tried to create a new kind of artificial intelligence. In March the same year the Berkley Initiative on Soft Computing (BISC) was created at the Berkeley Industrial Liason Program conference. According to BISC, software computing consists of fuzzy logic, neural network, evolutionary computing, etc. These methods are very suitable for solving personalization tasks. Soft computing methods could be used to perform research on the basis of qualitative metrics, so that indeterminable data (such as perceptions, sensations, assimilation, success rate) can be compared with real metrics resulting in good decisions in a given situation. Below we will look at the application of precisely such methods that use soft-computing means to model fuzzy uncertainties and, in particular, to look for personalization solutions when creating user profile models.

The purpose of this research is to present adequate methods for modeling a user profile in their role as a learner. Basic soft computing methods are considered due to their appropriate specificity. They can be used individually or in combination with other machine learning methods to meet the set goal.

1. SOFT COMPUTING METHODS FOR USER PROFILE MODELING

1.1. Fuzzy Logic (FL)

Fuzzy logic has the ability to capture unstructured or ambiguous information and to model it under conditions of uncertainty (Klir and Yuan, 1995). Unlike traditional methods, FL stems from fuzzy set theory which deals with reasoning that is more approximate than precisely derived from classical predicate logic (Yan, Power and Ryan, 1994). It is this specificity that enables FL to capture the uncertainty inherent in real data. Not only the students' personal interests and behavior should be taken into account when building a student's profile, but also the way teachers work, in order to maintain the balance between them and to achieve a higher level of results based on the student's achievements. In this regard, Yadav R. et al. (2011) propose a fuzzy expert system (NFES) that distinguishes between a high IQ student and a low IQ student. Its main purpose is to modify learning according to each student's pace. NFES has the capacity to make decisions, monitor the growth of each student and determine the next step in their learning (Pal, 2014). The Student Learning Assessment Model was created with the help of FL to evaluate students' academic achievements by gathering information and providing results for comparison with statistical value (Singh Yadav and Singh, 2011). Researchers also focus on evaluating teacher's performance because teachers are at the heart of student achievement (Moran, 2015). Through the use of FL, educators can assess a teacher more efficiently than the current procedures. A number of researchers have used fuzzy time series to predict and forecast student enrollments in higher education institutions (Singh, 2015; Jilani, Burney and Ardil, 2019). FL is also used for filtering. Fuzzy-filtering scientists offer a way to match filtered data to the consumer interests and preferences as a method of user personalization (Vrettos and Stafylopatis, 2001). Although FL is not a machine learning technique, due to its proven ability to capture uncertainty in humans and adapt it to the task of personalization, it is permissible to use collaborations between soft computing and machine learning methods when creating user models. Some examples of these combinations are Fuzzy Clusters (see section 1.4.), Fuzzy Association Rules, and Fuzzy Bayesian Networks. Through the Bayesian Networks, a model has been proposed to discover the different styles of student learning, as each student has their own learning behavior. The results are more accurate and stable over the time compared with the traditional methods. This model helps to model student's profiles with high accuracy (García *et al.*, 2007). It is also effective to capture the teacher's gaps in assessment in order to avoid making the same mistakes and to identify practices that will be useful in the future (Xenos, 2004).

Although the FL method is well suited for user profile modeling, it faces some challenges in real-world applications. The main one is that it does not have a data learning mechanism. This means that the knowledge about the field of application must be explicitly given by the designer. Neuro-Fuzzy Methods which will be discussed in another section (see section 1.5.), are emerging as an approach to alleviate this challenging situation.

1.2. Neural Networks (NN)

The neural network is an information processing approach that is inspired by the way the biological nervous system and the brain process information (Fausett, 1994). A key element of this paradigm is how information is processed. It consists of a large number of highly interconnected processing elements (neurons) working in unison to solve specific tasks (Haykin, 1998). Soft computing methods, in particular neural networks, can help to predict the content of elements in complex nonlinear cases (Tarasov *et al.*, 2018). NN can make sense from complex and/or inaccurate data or from models that are too complex to be explored by other computational methods. Another benefit is that they do not need initial knowledge of the problem being addressed. These characteristics make the NN a method for modeling human behavior and a suitable tool for creating user profile models. NN have been widely used to create user models, mainly for classification and recommendations, so that users with similar characteristics can be grouped together and create profiles to made. Bidel, Lemoine, and Piat (2003) provide some examples of classifying user models with NN, and Sas, Reilly, and O'Hare (2003) recommend using the NN method for predicting consumer behavior in a virtual environment. Due to the ability of NN to capture any type of knowledge, they are also used for filtering and forecasting tasks. The neural network can be used to provide forecasts that present new situations and answer questions. Beck, Jia, Sison, and Mostow (2003) model student behavior for an intelligent learning system.

Although the number of successful applications created with NN is significant, this method still has limitations in creating user profile models. The main obstacles are the training time it takes to create a model (in some cases, it can take hours or days) and the set of required data. Training time can cause inconvenience in dynamic model preparation. Although there are techniques that can re-qualify NN, when creating custom models it is usually re-qualified from scratch, ie. when there is more information, a new user or a new document, this is added to the system. Another disadvantage of NN is the limited interpretability of their solutions. While other techniques, to varying degrees, can be interpreted and manually modified, the representation of knowledge in the NN is not easy to interpret. As a result, their application is avoided when user-friendly models are needed.

1.3. Genetic and evolutionary algorithms (GA and EA)

Genetic and evolutionary algorithms are algorithms that include search and iterative optimization of the solution. They are based on the mechanism of natural selection in order to find the best possible algorithm for solving a task. GA can be seen as an evolutionary process and helps the exchange of the newly-discovered knowledge in the form of genes between the individuals, as well as a mutation, thereby helping to recover lost data or explore unexplored regions in the desired space of solutions.They start with a set of potential solutions - population-forming chromosomes. They use the solutions of one population to form a new one that is closer to the optimal solution of the problem under consideration (Potey and Sinha, 2015). They can be used to build effective classification systems, algorithms for finding the associative rules, and other similar tasks related to data collection. Their reliable search technique has given them a central position in data mining and machine learning. The approaches have been used primarily for recommendations that can capture consumer goals and preferences in the form of rules. Examples of this approach are given by Romero, Ventura, and de Bra (2003) for student modeling, to capture user preferences for improving web searches. They have also been applied for filtering and classification as well as creating models which predict student's achievemens. In the student's profile modeling, the primary role is played by the assessment of the individual student. This process can be analyzed through GA and helps to identify the most important factor affecting student's performance - their total achievement (Xing *et al.*, 2015). Teacher assessments also include student's evaluations that have been recorded throughout their academic careers. This process deals separately with evaluations obtained on different grounds - theoretical, practical and mathematical, which leads to more accurate results (Miranda Lakshmi, Martin and Prasanna Venkatesan, 2013). Genetic and evolutionary algorithms are more efficient than machine learning and data mining methods. This is because GA perform global searches and thus handle attribute interactions more successfully, whereas traditional methods use local search.

The method considered is suitable for searching in large and complex problem spaces but this creates a precondition for limitations both in its computing power and in relation to its potential for dynamic modeling and interoperable complexity.

1.4. Fuzzy Clusters (FC)

Fuzzy clustering has been intended as a method by which unstructured and unclassified information is structured into clusters based on any kinds of similarities. The clustering algorithm finds a set of concepts that cover all possible examples.One of the most widely used fuzzy clustering algorithms is the Fuzzy K-Means algorithm (Bezdek, 1981). It has been used to evaluate students' performance in relation to the entire academic career of teachers. The effectiveness of student's learning is based on the teaching methods of the teacher. This model helps to refine some of the limitations of the traditional model. Therefore, the K-Means clustering algorithm is also a suitable tool for analyzing and monitoring changes in student's work (Oyelade, Oladipupo and Obagbuwa, 2010). There are two types of clusters for creating user models: usage clusters and surfing clusters (Internet behavior). The users grouping has a tendency to create clusters of users that exhibit similar surfing patterns. In user modeling, FC are primarily used for recommendations and classification tasks. This is useful when personalized content is needed, such as demographic data or consumer interests.

The main problem faced by cluster techniques is how to define the concept of distance. In order to achieve this, thorough knowledge of the researched subject area is required. When the method is applied for modeling a user's profile, this task gets even more difficult because of the nature of the data: user preferences and interests, interactions and user behavior, success and progress when it concerns students, etc. On the other hand, this data may not be available digitally which is another limitation. The previously developed user profile models based on FC do not completely have the fuzzy character of the method. This is because the goal is more flexible and adaptable systems to be created and this means finding more meaningful ways to collaborate between different features and customization techniques, and grouping them into clusters.

1.5. Neuro-Fuzzy Method (NFM)

The neuro-fuzzy method is a combination between NN and FL. It uses NN for training and FL for generating fuzzy conclusions. It applies a process of fine-tuning of the membership rules and features of the inputs and outputs derived from the NN which are used in user profile modeling. This approach overcomes the disadvantages of NN and FL. NFM automate the process of transferring expertise or knowledge based on fuzzy rules (Jang, Sun and Mizutani, 1997). These methods are particularly suitable for applications where user interaction is desirable when designing or interpreting the model. Basically, FL-based systems include an automatic learning process provided by the NN. Along with fuzzy logic methods, NN have also been used for evaluation purposes. An Adaptive Neuro-Fuzzy Interference System (ANFIS) was developed to improve the speed, reliability and flexibility that were lacking in previous systems (Taylan and Karagözoğlu, 2009). This combination of NN and FL can give accurate numerical results to predict student's performance. By evaluating student's performance, it is easier to distinguish between the ones that are at risk. On the other hand, providing students with correct counseling and training will increase the graduation rate (Herzog, 2006).

The combination of NN with FL forms an appropriate method for creating user profile models. Drigas *et al.* (2004) propose an application of the recommendation task by offering job positions to unemployed people, using (as a basis) the data from the user profile and comparing it with the enterprise profile. Another group of researchers use the approach to solve the classification and recommendation problem by planning the web content of a course according to the student's level of knowledge (Magoulas, Papanikolaou and Grigoriadou, 2001). Although NFM are designed to combine the positives aspects of NN and FL, they still maintain some of their limitations. These mainly concern the time required for training and application of the dynamic modeling.

2. SUMMARY AND SELECTION OF METHOD FOR USER PROFILE CREATION

What has been presented so far demonstrates that each method has its own specific opportunities for creating a user-model depending on what it will be used for. The main advantage of soft computing methods is that they have the ability to capture connections and relationships from implicit data and model them for the purposes of the task at hand. Based on existing real data, soft computing methods are able to capture user plans, goals, and preferences. The knowledge gathered can be applied to model their future behavior and build a user profile model based on their general characteristics under the format of data structures. The models created will be able to use the ability of soft computing to mix different behaviors and capture decision-making processes in order to implement a personalized system that is more flexible and reasonable in terms of user interests.

The different methods offer different opportunities and can be used for different purposes, such as: FL - to derive goals and plans through a mechanism for imitation of the human decisions; NN- to present general characteristics resulting from the derived information and to create a stereotype of the user on this basis; FC - for grouping users into more than one stereotype at a time; NFM - to capture expert knowledge and tune it in order to make assumptions for the user. Soft-computing methods can be applied to build a profile model individually or in combination with traditional machine learning methods.

In Table 1, we summarize the characteristics of the methods presented in six dimensions.

Table 1

Characteristics of the basic soft computing methods for creating a user model

	Computer complexity	**Dynamic modeling**	**Data quantity**	**Uncertainty**	**Noise**	**Interpretability**
Fuzzy Logic	Medium	Yes	Missing	Yes	Yes	Low
Neural Networks	High	Yes	Large	Yes	Yes	High
Genetic/Evolutionary Algorithms	High	No	Missing	No	Yes	High
Fuzzy Clusters	Medium to high	No	Medium to large	Yes	Yes	High
Neuro-Fuzzy Methods	Medium to high	Yes	Medium to large	Yes	Yes	Medium to high

The first three dimensions cover the major issues that are involved in machine learning for creating a user model according to Webb, Pazzani and Billsus (2001). Namely: 1) Degree of computer complexity of the applicable method; 2) Dynamic modeling - whether the method allows the user profile model to be adjusted or changed during the working process; 3) Quality of the training data – it reflects the amount of data needed to create a reliable profile model. The next three dimensions are characteristic for soft computing methods: 4) Uncertainty - whether the methods can handle and process the uncertainty of human behavior when modeling a user profile; 5) Noise -

The ability to process noisy data, ie. whether the methods can handle and process the data noise; 6) Interpretability - the level of clarity of the results generated by the method, i.e. the extent to which the captured knowledge is easily interpretable by humans. Machine learning and DM researchers consider interpretability as a common problem and critical point in creating user models (Kim and Street, 2004).

The conclusion that can be drawn from Table 1 is that FL is a dynamic and flexible method but also moderately complex and difficult to interpret if used alone. NN have many advantages - they are easy to understand, process noisy data and data generated under uncertainty but require a lot of processing time. In contrast, NFM and FC hybrid approaches have a medium to high degree of computational complexity, have the ability to handle medium to large arrays of noisy data and uncertainty and the end result is easily interpretable. GA and EA prove to be the most inflexible and complex methods.

Table 2 presents the classification of soft computing methods in terms of possible interpretation requirements, addressing the five main types of tasks introduced at the beginning of this paper.

Table 2

Soft computing methods and requirements for interpretability of various tasks

Task	Required	Not required
Forecasting	*Neuro-Fuzzy Methods*; *GeneticAlgorithms*.	*Neural Networks*
Recommendation	*Neuro-Fuzzy Methods*; *Fuzzy Logic*.	*Neural Networks*; *Evolutionary Algorithms*; *Fuzzy Clusters*.
Classification	*Neuro-Fuzzy Methods*	*Neural Networks*; *Fuzzy Clusters*.
Clustering	-	*Fuzzy Clusters; Neural Networks.*
Filtering	*Fuzzy Logic*; *GeneticAlgorithms*.	*Neural Networks*; *Evolutionary Algorithms*.

Two possible interpretability values are considered: *Required* or *Not required*. They show whether the nature of the results obtained from the solution of the problem through the methods of soft computing are understandable (does not require explanation) or not (require explanation). They also show in which cases and under what methods additional actions and specialized knowledge in the field are required.

Both tables can be used in combination to facilitate the choice of method when creating a profile model. The process of choosing may start with an overview of Table 2 which indicates the clarity of the methods depending on the purpose of the task being solved and the results achieved. Then Table 1 should be used to make the final decision about which method or combination of methods will facilitate the creation of the model.

CONCLUSIONS

With each passing day consumers, incl. and students, expect more intelligent and personalized services. The key point in providing such services is to capture user expectations, attitudes and interests and, on their basis, to create a personal profile for each user which can be automatically upgraded and can plan consumer behavior in the future. Adequate creation of a user profile model depends on the implementation of adequate methods. Machine learning and DM methods are suitable for automatically creating and identifying profiles and interests. But their main disadvantage is that they lack the ability to capture and process the inherent uncertainty of human behavior. To address this aspect, soft computing methods are proposed as an adequate tool for creating personalized user models.

This review shows that one of the major problems with designing a user profile model is the lack of any type of standardization. In order to improve this situation, the current document proposes a set of guidelines that will form the framework for the design of user profiles based on soft computing approach.

Soft computing methods in combination with machine learning methods would achieve effective collaboration in modeling the natural complexity of human behavior and have great potential to create a user profile model.

REFERENCES

1. ALEXANDROVA, Y. and PARUSHEVA, S. (2017) Social Media in Higher Education from Students' Perspective. doi: 10.5593/sgemsocial2017/14/S04.092.
2. ATANASOVA, T. et al. (2019) Monographic library " Knowledge and business ", book 4 Intelligent Analysis of Students Dataset Publishing house " Knowledge and business " Varna.
3. BAKER, R. (2014) 'Educational Data Mining: An Advance for Intelligent Systems in Education', Intelligent Systems, IEEE, 29, pp. 78–82. doi: 10.1109/MIS.2014.42.
4. BECK, J. E. et al. (2003) 'Predicting student help-request behavior in an intelligent tutor for reading', Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science), 2702, pp. 303–312.
5. BEZDEK, J. (1981) Pattern Recognition With Fuzzy Objective Function Algorithms, Pattern Recognition with Fuzzy Objective Function Algorithms. doi: 10.1007/978-1-4757-0450-1.
6. BIDEL, S. et al. (2003) 'Statistical machine learning for tracking hypermedia user behavior', 2nd Workshop Machine Learning, Information Retrieval, and User Modeling, 9th Int. Conf. User Modeling, Pittsburgh, PA.
7. DRIGAS, A. et al. (2004) 'An expert system for job matching of the unemployed', Expert Syst. Appl., 26, pp. 217–224. doi: 10.1016/S0957-4174(03)00136-2.
8. EIRINAKI, M. and VAZIRGIANNIS, M. (2003) 'Web mining for Web personalization', ACM Trans. Internet Techn., 3, pp. 1–27. doi: 10.1145/643477.643478.
9. FAUSETT, L. (ed.) (1994) Fundamentals of Neural Networks: Architectures, Algorithms, and Applications. Upper Saddle River, NJ, USA: Prentice-Hall, Inc.
10. FRIAS-MARTINEZ, E. et al. (2005) 'Modeling human behavior in user-adaptive systems: Recent advances using soft computing techniques', Expert Systems with Applications, 29(2), pp. 320–329. doi: 10.1016/j.eswa.2005.04.005.
11. GARCHA, P. et al. (2007) 'Evaluating Bayesian networks' precision for detecting students' learning styles', Computers & Education, 49, pp. 794–808. doi: 10.1016/j.compedu.2005.11.017.

12. GUPTA, M. M., SINHA, N. K. and ZADEH, L. A. (2000) Soft Computing and Intelligent Systems: Theory and Applications. Elsevier Science (Academic Press Series in Engineering). Available at: https://books.google.bg/books?id=7-pQAAAAMAAJ.
13. HAYKIN, S. (1998) Neural Networks: A Comprehensive Foundation. 2nd edn. Upper Saddle River, NJ, USA: Prentice Hall PTR.
14. HERZOG, S. (2006) 'Estimating student retention and degree completion time: Decision trees and neural networks vis a vis regression', New Directions for Institutional Research, 2006, pp. 17–33. doi: 10.1002/ir.185.
15. JANG, J.-S., SUN, C.-T. and MIZUTANI, E. (1997) 'Neuro-Fuzzy and Soft Computing-A Computational Approach to Learning and Machine Intelligence [Book Review]', Automatic Control, IEEE Transactions on, 42, pp. 1482–1484. doi: 10.1109/TAC.1997.633847.
16. JILANI, T., BURNEY, S. M. A. and ARDIL, C. (2019) 'Fuzzy Metric Approach for Fuzzy Time Series Forecasting based on Frequency Density Based Partitioning'.
17. KIM, Y. and STREET, N. (2004) 'An Intelligent System for Customer Targeting:A Data Mining Approach', Decision Support Systems, 37, pp. 215–228. doi: 10.1016/S0167-9236(03)00008-3.
18. KLIR, G. J. and YUAN, B. (1995) 'Fuzzy Sets and Fuzzy Logic: Theory and Applications', Upper Saddle River: Prentice Hall, 13.
19. LEMMERICH, F., IFLAND, M. and PUPPE, F. (2011) Identifying Influence Factors on Students Success by Subgroup Discovery., EDM 2011 - Proceedings of the 4th International Conference on Educational Data Mining.
20. LEONG, C. K., Lee, Y. H. and MAK, W. K. (2012) 'Mining sentiments in SMS texts for teaching evaluation', Expert Syst. Appl., 39, pp. 2584–2589. doi: 10.1016/j.eswa.2011.08.113.
21. LOPEZ, M. I. et al. (2012) 'Classification via clustering for predicting final marks based on student participation in forums', Proc. of 5th Int. Conf. on Educational Datamining, pp. 148–151.
22. MAGOULAS, G., PAPANIKOLAOU, K. and GRIGORIADOU, M. (2001) 'Neuro-fuzzy Synergism for Planning the Content in a Web-based Course', Informatica, 25, pp. 39–48.

23. MIRANDA LAKSHMI, T., MARTIN, A. and PRASANNA VENKATESAN, V. (2013) 'An Analysis of Students Performance Using Genetic Algorithm', Journal of Computer Sciences and Applications, 1(4), pp. 75–79. doi: 10.12691/jcsa-1-4-3.
24. MORAN, A. J. (2015) A fuzzy logic approach to teacher performance measured by principal evaluations. Columbus State University. Available at: https://books.google.bg/books?id=3SeWswEA CAAJ.
25. NANDESHWAR, A., MENZIES, T. and NELSON, A. (2011) 'Learning patterns of university student retention', Expert Syst. Appl., 38, pp. 14984–14996. doi: 10.1016/j.eswa.2011.05.048.
26. NGUYEN, L. (2014) 'User Model Clustering', Journal of Data Analysis and Information Processing, 02(02), pp. 41–48. doi: 10.4236/jdaip.2014.22006.
27. OYELADE, J., OLADIPUPO, O. and OBAGBUWA, I. (2010) 'Application of k Means Clustering algorithm for prediction of Students Academic Performance', International Journal of Computer Science and Information Security, 7.
28. PAL, S. (2014) A Study of Academic Performance Evaluation Using Fuzzy Logic Techniques. doi: 10.1109/IndiaCom.2014.6828010.
29. POTEY, M. and SINHA, P. (2015) 'Review and Analysis of Machine Learning and Soft Computing Approaches for User Modeling', International journal of Web & Semantic Technology, 6, pp. 39–55. doi: 10.5121/ijwest.2015.6104.
30. ROMERO, C. et al. (2003) 'Discovering Prediction Rules in AHA! Courses', in Proceedings of the 9th International Conference on User Modeling. Berlin, Heidelberg: Springer-Verlag (UM'03), pp. 25–34. Available at: http://dl.acm.org/citation.cfm?id=1759957.1759965.
31. ROMERO, C. et al. (2013) 'Predicting Students' Final Performance from Participation in On-line Discussion Forums', Computer&Education, 68, pp. 458–472. doi: 10.1016/j.compedu.2013.06.009.
32. SAS, C., REILLY, R. and O'HARE, G. M. P. (2003) 'A connectionist model of spatial knowledge acquisition in a virtual environment', MLIRUM'03 2nd Workshop on Machine Learning, Information Retrieval and User Modelling at 9th International Conference on User Modelling. Available at: http://comp.eprints.lancs.ac.uk/2108/.

33. SINGH, P. (2015) ‘A brief review of modeling approaches based on fuzzy time series’, International Journal of Machine Learning and Cybernetics, 8. doi: 10.1007/s13042-015-0332-y.
34. SINGH YADAV, R. and SINGH, V. (2011) ‘Modeling Academic Performance Evaluation Using Soft Computing Techniques: A Fuzzy Logic Approach’, International Journal on Computer Science and Engineering, 3.
35. TARASOV, D. et al. (2018) Artificial neural networks selection for soil chemical elements distribution prediction, AIP Conference Proceedings. doi: 10.1063/1.5044054.
36. TAYLAN, O. and KARAGЦZOPLU, B. (2009) ‘An adaptive neuro-fuzzy model for prediction of student’s academic performance’, Computers & Industrial Engineering - COMPUT IND ENG, 57, pp. 732–741. doi: 10.1016/j.cie.2009.01.019.
37. VRETTOS, S. and STAFYLOPATIS, A. (2001) ‘A fuzzy rule-based agent for web retrieval-filtering’, Lecture Notes in Artificial Intelligence, pp. 448–453.
38. WEBB, G. I., PAZZANI, M. J. and BILLSUS, D. (2001) ‘Machine Learning for User Modeling’, User Modeling and User-Adapted Interaction, 11(1), pp. 19–29. doi: 10.1023/A:1011117102175.
39. XENOS, M. (2004) ‘Prediction and assessment of student behaviour in open and distance education in computers using Bayesian networks’, Computers & Education, 43, pp. 345–359. doi: 10.1016/j.compedu.2003.09.005.
40. XING, W. et al. (2015) ‘Participation-based student final performance prediction model through interpretable Genetic Programming: Integrating learning analytics, educational data mining and theory’, Computers in Human Behavior, 47, pp. 168–181. doi: 10.1016/j.chb.2014.09.034.
41. YAN, J., POWER, J. and RYAN (1994) Using fuzzy logic towards intelligent systems. New York, N.Y. Prentice Hall. Available at: http://library.lincoln.ac.uk/items/30925.
42. ZUKERMAN, I., ALBRECHT, D. and NICHOLSON, A. (2001) ‘Predicting Users’ Requests on the WWW’, UM. doi: 10.1007/978-3-7091-2490-1_27.