Recent Soft Computing Approaches to User Modeling in Adaptive Hypermedia

E. Frias-Martinez[1], G. Magoulas[2], S. Chen[1], R. Macredie[1]

[1]Department of Information Systems & Computing
Brunel University
Uxbridge, Middlesex, UB8 3PH United Kingdom
{enrique.frias-martinez,sherry.chen,robert.macredie}@brunel.ac.uk

[2]School of Computer Science and Information Systems
Birkbeck College, University of London
Malet Street, London WC1E 7HX United Kingdom
gmagoulas@dcs.bbk.ac.uk

Abstract. The ability of an adaptive hypermedia system to create tailored environments depends mainly on the amount and accuracy of information stored in each user model. One of the difficulties that user modeling faces is the necessity of capturing the imprecise nature of human behavior. Soft Computing has the ability to handle and process uncertainty which makes it possible to model and simulate human decision-making. This paper surveys different soft computing techniques that can be used to efficiently and accurately capture user behavior. The paper also presents guidelines that show which techniques should be used according to the task implemented by the application.

1 Introduction

Adaptive hypermedia (AH) can be defined as the technology that allows personalization for each individual user of a hypermedia application, its content and its presentation according to user preferences and characteristics [29]. The process of personalization of a hypermedia application is implemented through a decision making and personalization engine which adapts the contents according to a user model. In this context it is clear that the key element of an adaptive hypermedia application is the user model. The more information a user model has, the better the content and presentation will be personalized. We consider a user model as a set of information structures designed to represent one or more of the following elements [18]: (1) representation of assumptions about the knowledge, goals, plans preferences, tasks and/or abilities about one or more types of users; (2) representation of relevant common characteristics of users pertaining to specific user subgroups (stereotypes); (3) the classification of a user in one or more of these subgroups; (4) the recording of user behaviour; (5) the formation of assumptions about the user based on the interaction history and/or (6) the generalization of the interaction histories of many users into stereotypes. Fig. 1 presents the architecture of a generic AH system.

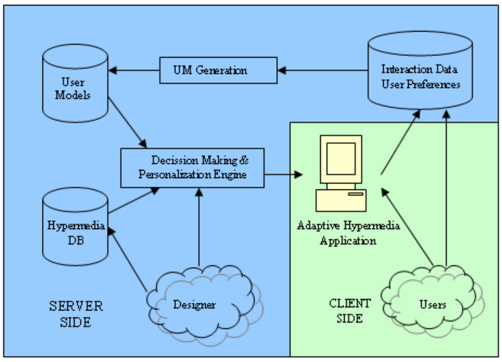

Fig. 1. Generic Architecture of an Adaptive Hypermedia Application.

The architecture of an adaptive hypermedia system is usually divided in two parts: the server side and the client side. The server side generates the user models from a data base containing the interactions of the users with the system and the personal data/preferences that each user has given to the system. These user models, in combination with a hypermedia database, are used by the "Decision Making and Personalization Engine" module to identify user needs, decide on the types of adaptation to be performed and communicate them to an adaptive interface. In this paper, we are going to focus on the "User Model (UM) Generation" module.

A typical user exhibits patterns when accessing a hypermedia system. Machine learning techniques can be applied to recognize regularities in user trails and to integrate them as part of the user model. The limitations of traditional machine learning techniques for modeling human behavior led to the introduction of Soft Computing (SC) for User Modeling (UM). SC technologies provide an approximate solution to an ill-defined problem and can create user models in an environment, such as a hypermedia application, in which users are not willing to give feedback on their actions and/or designers are not able to fully define all possible interactions. Human interaction is a key component of any hypermedia application, which implies that the data available will be usually imprecise, incomplete and heterogeneous. In this context SC seems to be the appropriate paradigm to handle the uncertainty and fuzziness of the information available to create user models [28]. The elements that a user model captures (goals, plans, preferences, common characteristics of users) can exploit the ability of SC of mixing different behaviors and capturing human decision processes in order to implement a system that is more flexible and sensible in relation to user interests. Different techniques provide different capabilities. For example, Fuzzy Logic provides a mechanism to mimic human decision-making that can be used to infer goals and plans; Neural Networks a flexible mechanism for the representation of common characteristics of a user and the definition of complex stereotypes; Fuzzy Clustering a mechanism in which a user can be part of more than one stereotype at the same time and NeuroFuzzy systems a mechanism to capture and tune expert knowledge which can be used to obtain assumptions about the user.

This paper presents a survey of different SC techniques available for modeling user behavior. The paper's intentions are (1) to give a perspective to the AH community about the potential of applying SC techniques to UM and (2) to give basic guidelines about which techniques can be useful for a given adaptive application.

2 A Taxonomy of Soft Computing-based User Models

User models can be classified according to two main elements: (1) *the granularity of the model*, a model can be created for each individual user (content-based modeling) or for clusters of users (collaborative modeling); and (2) *the type of task* for which the model is going to be used. We have defined four basic types of tasks: (i) *Prediction* (P), (ii) *Recommendation* (R), (iii) *Classification* (C) and (iv) *Filtering* (F). Prediction is the capability of anticipating user needs using past user behavior. A basic assumption is made with this approach: a user's immediate future is very similar to his/her immediate past. In the literature this is traditionally presented as *content-based filtering*. Recommendation is the capability of suggesting interesting elements to a user based on some extra information; for example from the items to be recommended or from the behavior of other users. In this context, recommendation is what in the literature is known as *collaborative filtering*. Classification builds a model that maps or classifies data items into one of several predefined classes. Filtering is defined as the selection of a subset of items that are interesting to a user from the original set of items. In general, any of the previous tasks can be implemented using knowledge stored in the different user model elements described in Section 1. For example, a filtering task can be implemented using knowledge stored in user preferences, or by classifying the user in a stereotype (or in more than one stereotypes). A prediction task can be implemented using the knowledge captured by the user's goals but also by the classification of the user in a stereotype, etc. In the following subsections we present a number of SC techniques and give examples of AH applications that employ the particular technique, specifying the task implemented and the granularity of the model.

2.1 Fuzzy Logic

Fuzzy Logic (FL) defines a framework in which the inherent ambiguity of real information can be captured, modeled and used to reason with uncertainty. An introduction to FL can be found in [17] and [40]. FL is not a machine learning technique, nevertheless due to its ability to handle uncertainty it is used in combination with other machine learning techniques in order to produce behavior models that are able to capture and to manage the uncertainty of human behavior. A traditional fuzzy logic inference system is divided into three steps: (1) fuzzification; (2) fuzzy inference; and (3) defuzzification. FL in UM does not necessarily realize these three steps, but a subset of them. Typically FL has been used to implement applications that are based on a recommendation task. In these applications FL provides the ability of mixing different user preferences and profiles that are satisfied to a certain degree. FL has been used to implement recommendation tasks [27], where fuzzy inference is used for recommendation purposes using user profiles obtained with hierarchical unsupervised clustering. In [1] fuzzy logic was used to model user behavior and give recommendation using this fuzzy behavior model. Although there is not strictly a fuzzy inference process, the stereotypes that characterize users are modeled using membership functions, and the recommendation process is done using a fuzzy AND operator. [32] presents a system designed to recommend products in an e-commerce site, according to how well this product satisfies user preferences. The score of an item (according to how much that item matches user interests) is done using an OWA (Ordered Weighted Averaging) operator. This family of operators allows the representation of fuzzy logic connectives and the aggregation of different user preferences.

FL has been used for filtering [38]. In this case FL provides a soft filtering process based on the degree of concordance between user preferences and the elements being filtered.

Table 1 summarizes relevant studies and applications of FL for UM. The columns detail the application, the data, the results obtained, the type of task (T) for which the SC technique was used and (I/G) if the system created a model for each individual (I) or for groups of users (G).

Table 1. Characteristics of some Fuzzy Logic- based User Modeling applications.

	Application	Data	Outcome	T	I /G
[27] Nasraoui and Petenes (2003)	Web recommendation system based on a fuzzy inference engine that uses a rule-based representation of the user profile.	12 days access log data of the Web site of the Dep. Comp. Eng. at the University of Missouri.	Fuzzy recommendation achieves high coverage compared to other machine learning solutions.	R	G
[38] Vrettos and Stafylopati (2001)	Agent for information retrieval and filtering in the context of e-learning.	Cranfield data set (www.cs.utk.edu/lsi) which includes 1398 documents, 225 queries and an average of 8.2 relevant documents per query.	Re-ranking the search according to user's profile.	F	I
[1] Ardissono and Goy (1997)	Introduction of personalization techniques in a shell supporting the construction of adaptive web stores.	Not Presented.	FL can be applied in electronic sales to produce personalized environments.	R	I
[32] Schmitt et al. (2003)	Recommendation of items of an e-commerce site to its users using a structure-based system.	Preferences specified by the user.	On-line demo: www2.dfki.de:8080 /mautmachine/html	R	I

2.2 Neural Networks

A Neural Network (NN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. Comprehensive introductions to Neural Networks can be found in [8] and [12]. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract complex patterns. A trained neural network can be thought of as an expert in the category of information it has been given to analyse.

NNs is a powerful method to model human behaviour Traditionally, NNs have been used for classification and recommendation in order to group together users with the same characteristics and create profiles. Some examples are in [5], which uses NN to classify user navigation paths, and [11], which uses Self Organizing Maps (SOM), an unsupervised NN that transforms highly dimensional data into a two dimensional grid, to classify documents based on a subjectively predefined set of clusters in a specific domain. NNs have also been used for recommendation in [31], which predicts the next step for a given user trajectory in a virtual environment, and in [2][3] which models student behavior for an intelligent tutoring system. NNs have also been used for filtering and prediction in [34] and [33] respectively. Table 2 summarizes some applications of Neural Networks for UM.

Table 2. Characteristics of some Neural Networks- based User Modeling applications.

	Application	Training Data	Outcome	T	I /G
[5] Bidel et al. (2003)	Classification and tracking of user navigation.	Data generated from an on-line encyclopedia.	A labelled approach to the problem produces better accuracy.	C	G
[31] Sas et al. (2003)	Prediction of user's next step in a virtual environment	30 users performed exploration and searching within the environment.	Very accurate predictions of the next step	R	G
[34] Shepperd (2002)	Adaptive filtering system for electronic news using stereotypes.	The Halifax Herald Ltd.	Very useful for readers with specific information needs.	F	I
[2][3] Beck and Woolf. (1998)	Construction of a student model for an intelligent tutoring system.	Data collected by the tutoring system	NN-based recommendation to each individual.	R	G
[33] Shavlik and Eliassi (2001)	Adaptive agents that retrieve and extract information by accepting user preferences in the form of instructions.	Instructions given directly by the user and user rated web pages.	Faciliates creating intelligent agents combining user instructions with machine learning.	F / P	I

2.3 Genetic Algorithms

Genetic Algorithms (GAs) are search algorithms based on the mechanics of natural selection [10]. A GA begins with a set of solutions (chromosomes) called the population. Solutions from one population are taken and used to form a new population, which are closer to the optimum solution to the problem at hand. GAs are a search strategy that is tailored for vast, complex, multimodal search spaces.

Table 3. Characteristics of some Genetic- based User Modeling applications.

	Application	Input Data	Outcome	T	I/G
[23] Min et al. (2001)	Profiling behavior of e-commerce customers.	Set of questions regarding size of company, e-purchasing usage, etc.	GA are useful for the discovery of profiles of e-commerce customers.	R	G
[30] Romero et al. (2003)	Discovering prediction rules from student usage information to improve web courses.	Stored information of a Linux course developed with AHA!.	The rules produced are better that traditional rule extraction algorithms.	R	G
[7] Fan et al. (2000)	Personalization of search engines using automatic term weighting	Cranfield text Collection and Federal Register (FR) text collection.	GA Automatic weighting improves the retrieval performance quite dramatically.	F	G

In general GAs have been used for Recommendation in the form of rules, which can capture user goals and preferences, because they perform a global search and cope better with attribute interaction than algorithms used in data mining, where the search is more local. Examples of this approach are [30] for student modeling and [23] for profiling of e-commerce customers. Nevertheless, they have also been applied for filtering [7]. Table 3 summarizes relevant applications of GAs for UM.

2.4 Fuzzy Clustering

In non-fuzzy or hard clustering, data is divided into crisp clusters, where each data point belongs to exactly one cluster. In Fuzzy Clustering (FC), the data points can belong to more than one cluster and associated with each data point are membership grades which indicate the degree to which it belongs to the different clusters. One of the key elements of any FC system is the definition of the concept of distance used for the creation of the clusters. The most widely used fuzzy clustering algorithm is the Fuzzy C-Means (FCM) Algorithm [4]. There are other algorithms, which basically are variations of the original FCM, like the Fuzzy c-Medoids Algorithm (FCMdd) or the Fuzzy c-Trimered Medoids Algorithm (FCTMdd) [19].

Table 4. Characteristics of some Fuzzy Clustering- based User Modeling applications.

	Application	Input Data	Outcome	T	I/G
[20] Lampinen and Koivisto (2002)	Obtain application profiles from network traffic data to manage network resources.	274000 samples of different applications from an edge router of a LAN network.	FCM produced better results than SOM. A method for the comparison of both solutions is also introduced.	R	G
[25] Nasraoui et al. (1999)	A new algorithm (CARD) to mine user profiles from access logs is proposed.	12 day log data of the Dep. of Comp. Eng.. at Univ. of Missouri.	CARD is very effective for clustering many different profiles in user sessions.	R	G
[16] Joshi et al. (2000)	Two algorithms to mine user profiles: FCM dd and FCTMdd.	CSEE logs of Univ. of Maryland	Both algorithms extract interesting user profiles. FCM is not able to handle noise as effectively as FCTM.	C	G
[19] Krishnapura et al. (2001)	Web access log analysis for user profiling using RFCMdd (Robust Fuzzy c-Medoids).	Five days of CSEE web server activity of Univ. of Maryland.	RFCMdd is very effective for clustering of relational data.	C	G

Typically, FC applied to UM has to use techniques that can handle relational data because the information used to create stereotypes (pages visited, characteristics of the user, etc.) cannot be represented by numerical vectors. In these systems the definition of distance is done using vectorial representations of user interactions with the adaptive hypermedia system. FC for UM, by its definition, is used for recommendation and classification tasks. [20], [25] and [26] are examples of applications that implement a recommendation task using FC. Examples of classification tasks are [16] and [19]. Table 4 summarizes some studies and applications of FC for UM.

2.5 Neuro-Fuzzy Systems

Neuro-Fuzzy systems (NFS) use NNs to extract rules and/or membership functions from input-output data to be used in a Fuzzy Inference System. With this approach, the drawbacks of NNs and FL, the black box behavior of NNs and the problems of finding suitable membership values for FL, are avoided. NFS automate the process of transferring expert or domain knowledge into fuzzy rules. [14] and [15] describe with more detail the basic concepts of NFS. One of the most important NFS is ANFIS [13], which has been used in a wide range of applications [6]. NFS are especially suited for applications where user interaction in model design or interpretation is desired.

NFS are basically FL systems with an automatic learning process provided by NN. The combination of NN and fuzzy sets offers a powerful method to model human behavior which allows NFS to be used for a variety of tasks. [21] and [35] use a NFS for Recommendation in an e-commerce site and for an on-line course respectively. [22] uses NFS to implement multi-attribute decision making with the purpose of planning the contents of a web-course according to the knowledge level of the student. [9] use NFS for prediction of a simulated aircraft control. Table 5 summarizes some studies and applications of NFS for UM.

Table 5. Characteristics of some NeuroFuzzy- based User Modeling applications.

	Application	Test bed	Outcome	T	I/G
[21] Lee (2001)	Mobile web shopping agent that finds products that suit user needs using a NFS and FL.	A test is implemented using a product data-base with 200 items and 8 categories.	Provides a more efficient result when compared with other solutions; processing time is shorter.	R	I
[35] Stathacopoulou et al. (2003)	Student Modeling	A set of simulated students.	High accuracy in the diagnosis of student problems during learning.	C/P	G
[22] Magoulas et al. (2001)	Intelligent decision making for recommending educational content in a web-based course depending on knowledge level	"Introduction to Computer Science" course of the Univ. of Athens.	Successful handling of fuzziness associated with the evaluation of learner's knowledge.	C/R	G
[9] George and Cardullo (1999)	Modeling of human behavior.	10 subjects collected data for the one dimensional compensatory task.	Generate a model of human behavior.	P	G

3 Criteria for the Selection of Techniques

Maybe seen from the preceding discussion, no SC technique is ideal for all situations. Each one captures different relationships among the data available. In this section we present guidelines to help decide which technique to use when developing an AH application. Table 6 summarizes the characteristics of the techniques presented along seven dimensions. The first four dimensions capture the main problems that machine learning for user modeling faces according to [39]: Computational Complexity, i.e. off-line processing; Dynamic Modeling, which indicates the suitability of the technique to change a user model on-the-fly; Labeled/Unlabeled, which reflects the need of labeled data; and Size of training data, which reflects the amount of data needed to produce a reliable user model. The remaining dimensions present other relevant information: the ability of the techniques to handle uncertainty (Uncertainty), i.e. to produce user model that takes into account the inherent fuzziness of user modeling; the ability to handle noisy data (Noisy Data), i.e. how noisy training data will affect the user model produced; and the interpretability (Interpret.) of the results, i.e. how easy is for a human to understand the knowledge captured.

Table 6. Characteristics of different Soft Computing techniques applied to User Modeling.

	Complexity	Dynamic Modeling	Labeled / Unlabeled	Size of Training Data	Uncertainty	Noisy Data	Inter-pret.
Fuzzy Logic	Med	Yes	N/A	N/A	Yes	Yes	High
Neural Networks	High	Yes	Both	High	Yes	Yes	Low
Genetic Algorithms	High	No	N/A	N/A	No	Yes	Low
Fuzzy Clustering	High/Med	No	Both	Med/High	Yes	Yes	Low
Neuro-Fuzzy	High	Yes	Labelled	Med/High	Yes	Yes	Med/High

For example, NNs have a high training complexity, although they can have a real-time response time. NFS have a High/Medium interpretability, which depends on the architecture of the system, for example ANFIS produce systems with high interpretability. Traditional GAs are not able to cope with dynamic modeling problems, nevertheless some recent approaches present dynamic modeling using evolutionary computation for specific problems [36]. Two are the main criteria that determine the soft computing technique that is going to be used by a specific adaptive application: (1) the type of task and (2) the interpretability needed for the results. As was previously discussed the main types of task are: Prediction; Recommendation; Classification; and Filtering. There are two possible values for Interpretability, needed or not relevant. The first one expresses the necessity of having a human understandable output while the second one states that this factor is not important. Table 7 presents guidelines related to what soft computing techniques are useful considering the criteria previously introduced. The techniques are classified according to the set of references used in this study. This does not necessarily mean that the techniques cannot be used to implement other types of tasks. For example, NNs are basically used for task that need no interpretability. Nevertheless some recent approaches describe techniques to extract the knowledge embedded in NN [37]. The combination of Tables 6 and 7 can be used to guide a choice of which technique to use for user modeling in an AH system. First, Table 7 can be used to identify the set of techniques suitable for the adaptive application and, after that, Table 6 can be used to refine the search and take the final decision.

Table 7. Techniques recommended for each combination of the decision variables.

Task	Interpretability	
	Needed	**Not Needed**
Prediction	NeuroFuzzy	Neural Networks
Recommendation	NeuroFuzzy Fuzzy Logic	Neural networks Genetic Algorithms Fuzzy Clustering
Classification	Neuro Fuzzy	Neural Networks Fuzzy Clustering
Filtering	Fuzzy Logic	Neural Networks Genetic Algorithms

4 Conclusions

This paper has presented a brief review of the state of the art of SC techniques use within the area of adaptive hypermedia systems. The review demonstrates that one of the main problems that the development of AH faces is the lack of any kind of standardization for the design of user models. In order to improve this situation this paper has tried to give a set of guidelines that formalize the design of user models using a SC approach. It is our opinion that the future of User Modeling is in hybrid systems. As has been shown, each technique captures different elements of user behavior. The combination of these SC techniques among themselves and with other machine learning techniques, will provide a useful framework to efficiently capture the natural complexity of human behavior.

Acknowledgments
The work presented in this paper is funded by the UK Arts and Humanities Research Board (AHRB grant reference: MRG/AN9183/APN16300).

References

1. Ardissono, L., Goy, A.:Tailoring the Interaction with Users in Electronic Shops, Proceedings of the 7th International Conference on User Modeling, UM97, Banff, Canada, 1997
2. Beck, J., Jia, P., Sison, J., Mostow, J.: Predicting Student Help-Request Behavior in an Intelligent Tutor for Reading, Proc. of the 9th Int. Conf. on User Modeling, LNAI 2702, pp. 303-312, 2003
3. Beck, J.E., Woolf, B.P.: Using a Learning Agent with a Student Model, LNCS 1452, 1998
4. Bezdek, J.C.: Pattern Recognition with Fuzzy Objective Function Algorithms, Plenum Press, 1981
5. Bidel, S, Lemoine, L., Piat, F.: Statistical machine learning for tracking hypermedia user behavior, 2nd Workshop on Machine Learning, Information Retrieval and User Modeling, 9th Int. Conf. in UM, 2003
6. Bonissone,P., Badami, C., Chiang, X.: Industrial Applications of Fuzzy Logic at General Electric, Proceedings of the IEEE, 83(3), pp. 450-465, 1995
7. Fan, W., Gordon, M. D., Pathak, P.: Personalization of Search Engine Services for Effective Retrieval and Knowledge management. In Proc. Of the 21st Int. Conf. on Information Systems, pp. 20-34, 2000
8. Fausett L., Fundamentals of Neural Networks, Prentice-Hall, 1994
9. George G., Cardullo, F.: Application of Neuro-Fuzzy Systems to Behavioral Representation in Computer Generated Forces, Proc. 8th Conf. on Comp. Generated Forces, pp. 575-585, 1999
10. Goldberg, D.: Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley, 1989
11. Goren-Bar, D., Kuflik, T., Lev, D., Shoval, P.: Automatic Personal Categorization Using Artificial Neural Networks, 8th International Conference on User Modeling 2001, LNAI 2109, pp. 188-198, 2001

12. Haykin S., Neural Networks, 2nd Edition, Prentice Hall, 1999
13. Jang, J.S.: ANFIS: Adaptive-Network-Based Fuzzy Inference Systems, IEEE Transactions on Systems, Man, and Cybernetics, Vol. 23(3), pp. 665-685, May 1993.
14. Jang, J.S.R., Sun, C.T.: Neurofuzzy modelling and control,in *Proceedings IEEE*, 1995
15. Jang, J.S.R., Sun, C.T:*Neurofuzzy and Soft Computing*, Prentice Hal, 1997
16. Joshi, A., Joshi, K., Krishnapuram, R., On mining Web Access Logs, in Proceedings of the ACM-SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery, pp. 63-69, 2000
17. Klir, J., Yuan,B.: Fuzzy Sets and Fuzzy Logic. Theory and Applications, Prentice Hall, 1995
18. Kobsa, A.: Generic User Modeling Systems, User Modeling and User-Adapted Interaction 11, 49-63, 2001
19. Krishnapuram, R., Joshi, A., Nasraoui, O., Yi, L., Low-Complexity Fuzzy Relational Clustering Algorithms for Web Mining, in IEEE Transactions on Fuzzy Systems, Vol. 9 (4), pp. 595-608, 2001
20. Lampinen, T., Koivisto, H.: Profiling Network Applications with Fuzzy C-Means Clustering and Self-Organising Map, Int. Conf. on Fuzzy Systems and Knowledge Discovery, 2002
21. Lee, R.S.T.:iJADE IWShopper: A New Age of Intelligent Web Shopping System Based on Fuzzy-Neuro Agent Technology. In Web Intelligence: Research and Development, LNAI 2198, pp. 403-412, 2002
22. Magoulas, G.D., Papanikolau, K.A., Grigoriadou, M.: Neuro-fuzzy synergism for planning the content in a web-based course, Informatica Vol. 25(1), 2001
23. Min, H., Smolinski, T., Boratyn, G.: A GA-based Data Mining Approach to Profiling the Adopters of E-purchasing, Proc. of the 3rd Int. Conf. on Information Reuse and Integration , pp. 1-6, 2001
24. Nasraoui, O., Cardona, C., Rojas, C., Gonzalez, F.: Mining Evolving User Profiles in Noisy Web Clickstream Data with a Scalable Immune System Clustering Algorithm. In Workshop Notes of WEBKDD 2003: Web Mining as Premise to Effective&Intelligent Web Applications, pp. 71-81, 2003
25. Nasraoui, O., Frigui, H., Joshi, A., Krishnapuram, R.: Mining Web Access Logs Using Relational Competitive Fuzzy Clustering, 8th Intl. Fuzzy Systems Association World Congress - IFSA 99, 1999
26. Nasraoui, O., Krishnapuram, R.: Extracting Web User Profiles Using Relational Competitive Fuzzy Clustering. In International Journal on Artificial Intelligence Tools, Vol. 9(4), pp. 509-526, 2000
27. Nasraoui, O., Petenes, C.: Combining Web Usage Mining and Fuzzy Inference for Website Personalization. In WEBKDD 2003: Web Mining as Premise to Effective Web Applications, pp. 37-46, 2003
28. Pal, S.K., Talwar, V., Mitra, P.: Web Mining in Soft Computing Framework: Relevance, State of the Art and Future Directions, IEEE Transactions on Neural Networks, Vol. 13(5), pp.1163 - 1177, 2002
29. Perkowitz, M., Etzioni, O.: Adaptive Web Sites. Communications of the ACM, Vol. 43(8), 152-158, 2000
30. Romero, C., Ventura, S., de Bra, P.: Discovering Prediction Rules in AHA! Courses, Proceedings of the 9th International Conference on User Modeling, LNAI 2702, pp. 25-34, 2003
31. Sas, C., Reilly, R., O'Hare, G.: A Connectionist Model of Spatial Knowledge Acquisition in a Virtual Environment. In 2nd Workshop on Machine Learning, Information Retrieval and User Modeling, 2003
32. Schmitt, C., Dengler, D., Bauer, M.: Multivariate Preference Models and Decision Making with the MAUT Machine, in Proc. of the 9th Int. Conf. on User Modeling, LNAI 2702, pp. 297-302, 2003
33. Shavlik, J., Eliassi, T.: A System for building intelligent Agents that Learn to retrieve and Extract Information. In International Journal on User Modeling and User Adapted Interaction, 2001.
34. Sheperd, A., Watters, C., Marath, A.T.: Adaptive User Modeling for Filtering Electronic News. In Proc. of the 35th Annual Hawaii Intl. Conf. on System Sciences (HICSS-02), Vol. 4, 2002
35. Stathacopoulou, R., Grigoriadou, M., Magoulas, G.D.: A Neuro-fuzzy Approach in Student Modeling, Proceedings of the 9th Int. Conf. on User Modeling, UM2003, LNAI 2702, pp. 337-342, 2003
36. Sternberg, M., Reynolds, R.G.: Using cultural algorithms to support re-engineering of rule-based expert systems in dynamic performance environments: a case study in fraud detection Sternberg, IEEE Transactions on Evolutionary Computation ,Vol. 1(4), pp. 225-243, 1997
37. Ticlek, A.B., Andrews, R., Golea, M., Diederich, J.: The truth will come to light: directions and challenges in extracting the knowledge embedded within trained artificial neural networks IEEE Trans. on Neural Networks, Vol. 9(6), pp. 1057-1068, 1998
38. Vrettos, S., Stafylopatis, A.: A Fuzzy Rule-Based Agent for Web Retrieval-Filtering. In Web Intelligence: Research and Development, LNAI 2198, pp. 448-453, 2002
39. Webb, G.I., Pazzani, M.J., Billsus, D.: Machine Learning for User Modeling. In User Modeling an User-Adapted Interaction, (11), pp. 19-29, 2001
40. Yan, J., Ryan, M., Power, J.: Using Fuzzy Logic, Prentice Hall, 1994