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Semantic Predictive Model of Student Dynamic Profile Using Fuzzy Concept

T. Sheeba[a], Reshmy Krishnan[b]

[a]*Research Scholar, Department of Computer Science and Engineering, Karpagam University, Coimbatore-641021, India*
[b]*Associate Professor, Department of Computing, Muscat College, P.O.Box: 2910, P.C:112, Ruwi, Sultanate of Oman*

Abstract

Student profile describes the best way a student prefers to learn. It includes information on student's characteristics such as background knowledge, learning preference, styles, interest, goals etc.The major challenge that the students face in learning system is that they are unable to retrieve relevant information based on their requirements. One of the methods used to obtain the requirement of the students is to construct an efficient student profile which would reflect the true student needs. The proposed work is to develop an intelligent ontology-based dynamic student profile that provides semantic retrieval using fuzzy concepts. The approach starts with the collection of both static and dynamic data of students. The dynamic dataof students particularly student interest and learning style are obtained by weblog analysis using algorithms such as semantic based representation using WordNet and decision tree classifier algorithm based on Felder-Silverman learning style model (FSLSM). The retrieved data is then used to construct student profile using ontology in which automatic student profile updating is obtained using ontology -based semantic similarity algorithm using WordNet. Finally, semantic retrieval of student information from ontology is achieved by integrating fuzzy concepts using fuzzy linguistic variable and 'fuzzy IF THEN' rules. Fuzzy linguistic variable is used to make precise representation on the existing ontology concepts which facilitate more specific classification and semantic retrieval of information. The predictive model of student profile is designed with the implementation of 'fuzzy IF THEN' rules using forward chaining reasoning process in the existing ontology model. The inference engine predicts the preference of a new student based on the reasoning process done for specific conditions particularly on student interest and learning style. The experiments were performed using NetBeans IDE, OWL API and Protégé 4.2 beta editor. The experiment result shows the successful completion of student profile generation, updating, fuzzy semantic retrieval and prediction through utilization of fuzzy concepts in student profile ontology.

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*Keywords:*Dynamic studentprofile; Ontology; WordNet; Reasoning; Fuzzy linguistic variable; Fuzzy IF THEN rules

1. Introduction

A student profile [3] represents a structure containing both direct and indirect information relating to student's background, goals, interest and preferences. The student profile [16] plays a significant role in identifying a student's point of view to access and retrieve relevant information. It form the most appropriate and good representation of selecting facilities that suit the best to the student's requirements which in turn enhance the usage of learning content. It provides support to match the student's profiles against information retrieved from the system. Hence, it is important to construct an effective student profile that forms the basis of most recommender systems. The most important issue [14] to be considered in the student profile construction process is the notions of the semantic web. Semantic Web provides fixed set of meta-data which describe the semantic characteristics of student in the student profile and also support sharing of distributed student profile between systems. It mainly depends on formal ontologies [14] to structuredata for the purpose of comprehensive and transportable machine understanding. The use of ontology in learning system is a more intelligent approach in the new era of education. The utilization of ontologies in student profiling has gained lot of attention in recent years as it enables student interest and learning preference detection indirectly using log files which were not directly observed in student's behavior and allows for inference to be employed.

However, a typical ontology representation [5] is still not sufficient for efficient retrieval of information as it does not help to specify imprecise and uncertain information due to its support in conceptual formalism. In order to achieve semantic retrieval, fuzzy linguistic variable and 'fuzzy IF THEN' rules are used in existing ontology which would help for classification, semantic retrieval and prediction of student preference in a precise way.

This paper aims at proposing an approach to improve the representation of a studentprofile based on static and dynamic data of the students. To do so, static and dynamic data of student are collected along with semantic representation of student interest using WordNet; automatic learning style classification using decision tree classifier based on FSLSM, ontology construction, automatic ontology updating and semantic retrieval, a combination that, can suitably construct student profiles for learning system to consistently reflect both implicit and explicit details of the students.

2. Literature Review

There are several works proposing user profile creationin different areas. A user profile [16] is constructed automatically using the learning objects of a studentusing fuzzy ontology along with profile updating in AGORA E-Learning platform. An ontology based user profile [12] is developed using fuzzy clustering techniques which would help to group users with different degree of accuracy and also shows user profile representation by means of more than one ontologies.A user profile [2] is constructed using information collected fromdifferent search spaces such as blog, personal webpage, organization sites, and other sites. The constructed profile is used to find the group of users having similar interest using similarity score by collaborative user methods and an ontology matching approach.

The use of fuzzy concept in ontologyhelps for semantic retrieval of information from ontology. Semantic retrieval [5] [6] from ontology is performed on semantic web using the concept of fuzzy linguistic variable and successfully applied in both electronic commerce and traffic information service. FuzzyDL [4], an expressive fuzzy ontology reasoner, is described with unique features,it's various possibilities for fuzzy ontology representation in different interfaces, its implementation with reasoning servicesand a comparison with other fuzzy ontology reasoners.

Even many researchers focus on building user profiling, a complete profiling with full details of user data supporting semantic web technology,semantic retrieval and prediction which are the important requirements of learning system is not focused in the existing research works. Hence, the proposed approach is to construct a complete ontology based student profile that captures the full details of the studentwith semantic retrieval in order to satisfy the learning requirement of the student in a learning system in an efficient way.

3. Methodology

A student profile is a profile which includes all the basic information about the student. The proposed system architecture shown in Fig. 1 composed of mainly 4 phases: data collection, data preprocessing, knowledge management and fuzzy semantic retrieval.

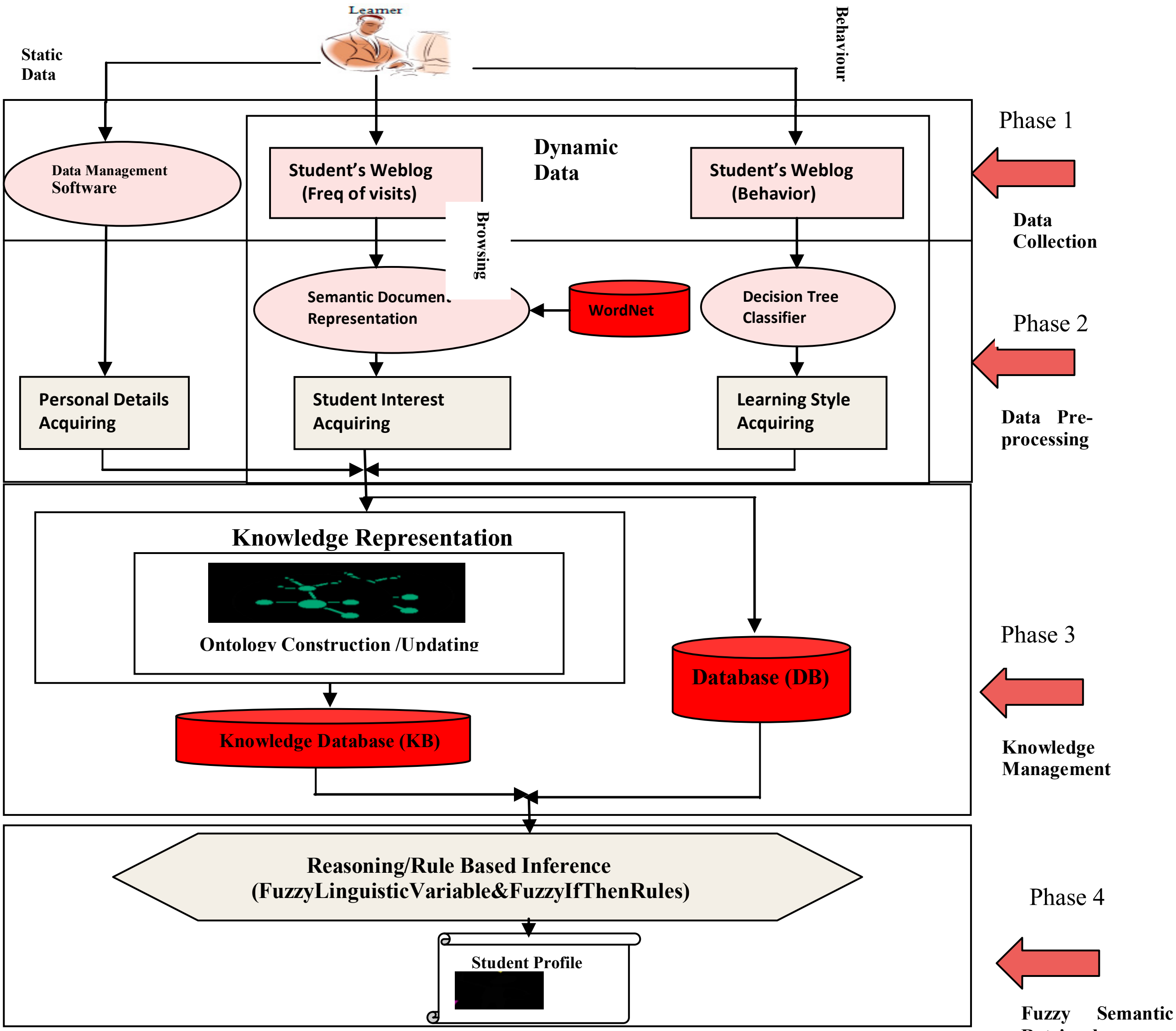

Fig. 1.systemarchitecture of proposed approach

The approach starts with the collection of both static and dynamic data of student. Static data is a fixed set of data that does not change as it is obtained from the database management software used in the institution. Dynamic data is continually updated and may change after updated. It is obtained by analyzing the weblog files obtained from the learning management system (LMS), Moodle used in the institution. The processed data is then used to construct semantic student profile using the concept of ontology.

The main focus of the paper is the 'knowledge management' and 'fuzzy semantic retrieval' phase of Fig.1.The knowledge management phase is usedto construct semantic student profile using ontology with automatic updating.Thefuzzy semantic retrieval phase is used to achieve retrieval and classification using fuzzy linguistic variable and prediction using 'fuzzy IF THEN rules'-based inference through forward chaining reasoning process. The basic functionality of proposed approach is explained in the below sections:

3.1. Knowledge management

3.1.1. Semantic student profile construction

The construction of student profile makes use of the static and dynamic student data stored in the database. Ontology is used to construct student profile structure by a set of concepts. Ontology [16]is used as a standard knowledge representation of a domain. It is a conceptualization of a domain into a machine-readable format comprising of attributes, entities, relations and axioms. Ontology-based semantic student profile has been used to improve the performance of various tasks such as classification, retrieval, filtering etc. The proposed system involves the following basic steps for ontology development:i)enumerate important concepts and terms in ontologyii) define concepts, relation of concepts iii) define individuals of concepts iv) implement and v) evaluate the ontology to check for accuracy. The language used for the development of ontologyuses OWL2(Web Ontology Language)[16]which is the language mainly used for ontology development. This language facilitate the processing of the content of information and greater machine interpretability of web content.Itis the logical extension of OWL language and deals with weaknesses in the expressiveness of OWL, and also facilitates integration of new features requested by users.

3.1.2. Student profile updating

As the constructed ontology includes dynamic data of student which may change in due time, it is necessary to update the ontology automatically to incorporate dynamic characteristics such as changing interest and style.

Algorithm

Input: Term to be updated

Output: Term updated in student profile ontology based on similarity score

1. Get the term to be updated in student profile ontology.
2. Get Part of Speech 'noun' of the term from WordNet.
3. Compute the semantic similarity between two terms using information content approach.
4. Find the term with high relevance score which implies high similarity between two terms.
5. Return the term having higher similarity score.
6. Search the word in student profile ontology as:
   a. Check if the word is the root or not.

i. If Yes
   1. Find the position and depth of new term.
   2. Add the concepts to the student profile.

ii. If No and is not the Leaf.
   1. Find the position and depth of new term.
   2. Add the concepts to the student profile.

iii. If No and is the Leaf.
   1. Find the position and depth of new term.
   2. Add the concepts to the student profile.

Fig. 2.algorithm of student profile updating

The proposed system uses the efficient method of ontology based semantic similarity using WordNet to compare the terms identified for the student with the terms on the student profile. This measure of semantic similarity depends on the structure of WordNet which have been widely used in natural language processing. WordNet [15] is a large lexical ontology database of English language that includes four parts of speech (POS) such as nouns, verbs, adverb and adjectives which represent the function of words and the way words work in a sentence. In this database, the lexical categories are organized into synsets (list of synonyms terms or concepts). The synsets are connected to other synsets through explicit relations to form a hierarchy of concepts.

The algorithm of student profile updating process is shown in Fig. 2. The process starts with observing the changes in the database containing both static and dynamic data of the student. If any new concept c1 is noted, then WordNet concept c2 which is almost similar to the new concept c1 is identified. Then information content semantic similarity is computed between two concepts c1, c2 given by the equation (1): res (c1, c2) = IC (LCS (c1, c2)) (1)
where c represents the maximum information content shared by concepts c1 and c2. The output of this measure gives a numeric score that signifies the degree to which the two concepts are similar or not. The higher the score is, the more similar the meaning of the two words. Then the position of concept is determined and then inserted into the student profile ontology.

3.2. Fuzzy semantic retrieval

Semantic retrieval and prediction is achieved from the constructed ontology by applying fuzzy concept in the form offuzzy linguistic variable and 'fuzzy IF THEN rules'. Fuzzy linguistic variables are applied to the existing concepts of student profile ontology in order to make distinction on the imprecise and vague representation of concepts, thereby making classification and retrieval of information in student profile in a more specific and precise way. It is defined as a variable of the system whose values are usually words, phrases or sentences in an artificial language, rather than numerical values. Initially a fuzzy set is created including the linguistic variables of each concept in the student profile ontology which are then defined by membership functions.The basic definition [5] of linguistic label ontology is given by:a linguistic label ontology is a 4-tuple O_F= (c_a, CF, F, U), where

c_a = is a concept on abstract level e.g., age
C_F = is the set of fuzzy concepts which describes all values of $c_{a.}$
F =is the set of membership functions at U.
U=is the universe of discourse, U = [0,100]).(2)

An example of linguistic labels ontology for the proposed system is given by: O_F = (c_a =age of student, C_F = {youngster, youth, middle-aged, midlife, adult, old}, where "youngster" ≤ "midlife" ≤ "old", F is the membership functions and U = [0,100]).

Reasoning plays an important role in the implementation of knowledge based systems. It is used to generate conclusions from available knowledge. In the proposed system, rule-based reasoning is used to predict the preference of new student based on the input and 'fuzzy IF THEN rules'stored in the knowledge base, particularly on student interest and learning style. The two main strategies used for reasoning are forward and backward chaining. Forward chaining starts withthe initial existing facts and apply rules to derive new conclusion, while backward chaining starts with the desired conclusion, and work backwards to find supporting facts. 'Fuzzy IF THEN rules' are applied to the constructed semantic profile for making prediction of preference for new student using the concept of reasoning as shown in the system architecture of Fig. 1. The proposed system uses forward chaining reasoning strategy to evaluateall the 'IF THEN'rules in the rule base until an exact rule match is found in order topredict the preference for the new students. The final conclusion would help to classify, retrieve and predict preference to the students based on their interest and style which would satisfy the requirements of learning system.

4. Results and Discussion

The proposed approach was experimented on real time students' data set of approximately around 300 students collected from Moodle, the LMS of institution over a period of three months for five online courses from computing department. The five online courses registered in Moodle LMS for experimentation are “networking”, “network operating system”, data structures”, “multimedia” and “introduction to programming”.

4.1. Knowledge management

4.1.1. Semantic student profile construction

The input is the student profile data stored in the database including static data (id, name, profession, date of birth, phone number, place of birth, email, nationality, education) and dynamic data (student interest,and learning style). This input is first read in the java coding and then OWL API (Application Programming Interface)is used to provide access to the OWL model and elements (classes, properties and individuals)of ontology. The created OWL file is opened in the protégé 4.2 beta editor to view the ontology. The created ontology consists of both static and dynamic data which are represented using four main components (Fig.3.) ofstudent profile domain like classes, properties (object property, data property) and named individuals.

- **Classes:**denote a set of concepts from a domain. The classes created are id, name, education, phone no, profession, interest, learning styleetc.
- **Properties:**indicate attributes and relationship between classes.
  - Object Property: relationship between two classes. Example: <has studnat>Omani<has education>diploma.
  - Data Property:describe the relation between primitive data type and classes. Example <has email> 12078@email.muscatcollege.in
- **Named Individuals:**represent objects which are members of a class. It take the values of the created classes such id, name, education,date of birth, email, phone no, profession, nationality, interest, learning style etc. from the database. Example: <stud_name>; <pob>; <interest>; <profession>.

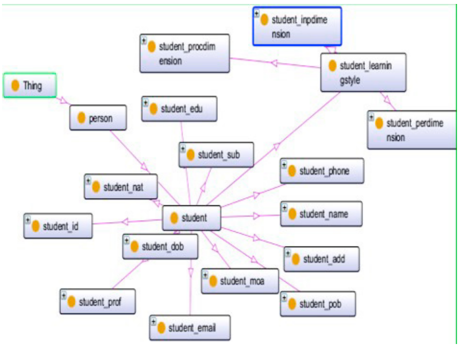

Fig. 3. (a) ontografview of ontology

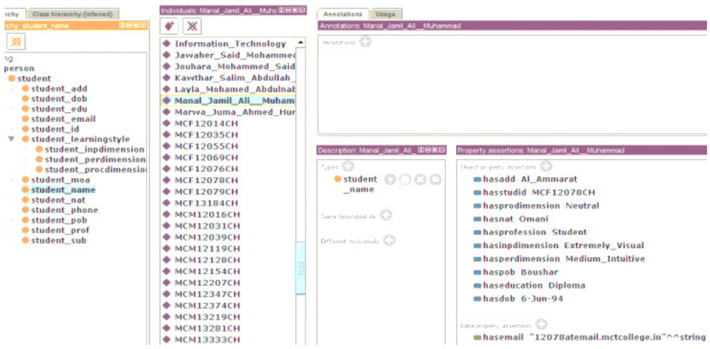

Fig. 3. (b) four component of ontology.

4.1.2. Studentprofile updating

In the proposed approach, ontology based semantic similarity using WordNet is used to compare students’ new identified data with the concepts in student profile ontology.Initially, similarity is calculated between all the classes in the student profile ontology and the new value using Resnik (res) information content semantic similarity. NetBeans IDE is used to code the updating algorithm using java programming language.

For experimentation, two ontologies are used. One is the student profile ontology and another is the WordNet ontology. For example, to add one new data ‘Mastersdegree’ with the existing student profile ontology, the first step is to find the similarity between the new data and existing concept in the student profile ontology in order to find the most suitable position to add the data. Next step is to find the depth of two words, and finally insert the data into theontology. Table 1.presents the result of the information-based semantic similarity measures (Resnik (res) which shows that ‘Diploma’ and ‘Bachelor degree’ are more similar to ‘Masters_degree’. The position of ‘Masters’ relative to ‘Diplomate’ in WordNet is evaluated and a negative value (depth (Masters) depth (Diplomate) = 13 – 15 = - 3) is obtained. Therefore, ‘Masters’ are added with ‘Diplomate’ as shown in Fig. 4.

Table 1.Result of Insertion of "Masters" in Student Profile Ontology.

Student profile terms	Semantic Similarity Score (res)	Position	Relation between two concepts
person	1.9033		
student	1.9033		
id	0.0		
name	0.0		
Mode	0.0		
DOB	0.0		
Email	0.0		
PhoneNo	0.0		
Education	0.0		
Profession	0.0		
Address	1.1692		
Place of Birth	1.1692		
Nationality	0.0		
Learning Style	0.0		
Learner Interest	0.0		
Bachelor degree	5.4219		
Diplomate	6.1028	-3	'Masters' added with 'Diplomate'

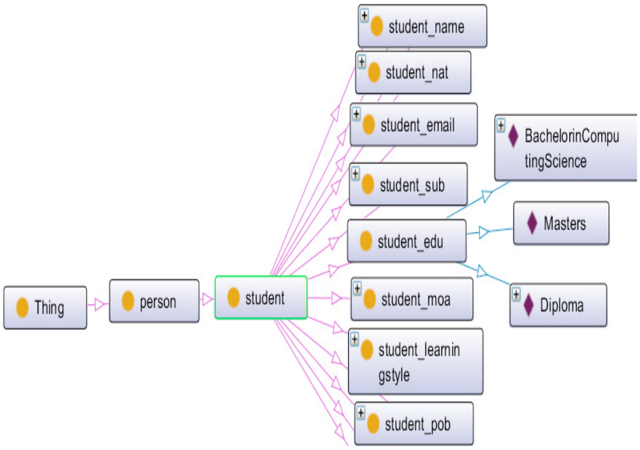

Fig. 4.existingstudentprofile ontology after adding 'Masters'

4.2. Fuzzy semantic retrieval

To achieve an efficient semantic retrieval from student profile, the proposed system uses fuzzy logic approach in the form of 'fuzzy linguistic variable' and 'fuzzy IF THEN rules' in the constructed ontology. Initially, the student profile ontology is taken as input which contains the crisp value of student attributes such as name, id, date of birth, nationality, education, qualification, profession, interest, learning style etc. These crisp values are converted into fuzzy values by assigning various linguistic variables.Some of the main fuzzy linguistic variable ontologies used in the system are as follows:O1= (age, {adult, middle-aged, old …});O2= (education, {highschool, diploma, bachelor, masters……}); O3= (profession, {student, manager, engineer, administrator …}). The membership values are then assigned to each possible individual of linguistic variable in the universe of discourse of fuzzy set. Based on the membership values, the final result is displayed for the selected values.SPARQL is the query language used in protégé to operate with ontologies. Fig. 5 shows the sample result of classification obtained using SPARQL query for the students whose date of birth comes under the age group namedas 'middle- aged'.

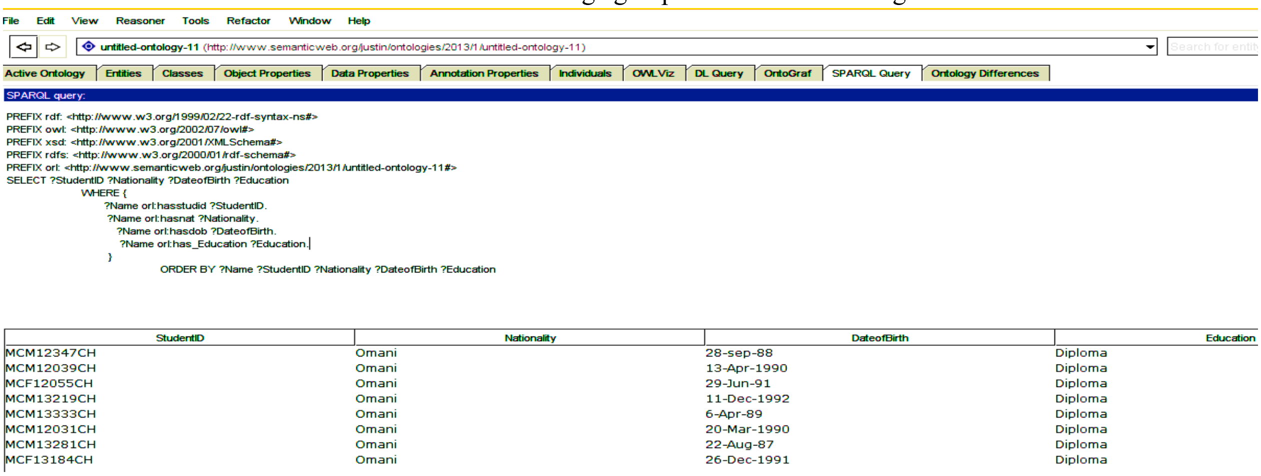

Fig. 5.sampleresult of SPARQL query

The application of fuzzy linguistic variable provides better information retrieval and more specific classification thereby providing an accurate judgment on the fields used in student profile ontology.

Fuzzy logic is also applied for rule based reasoning in the form of 'fuzzy IF THEN rules' which is used to predict the learning preference based on student interest and learning style of students. The rules give an additional level of expressivity of Web Ontology Language (OWL). The rule identifies the input and output of the system and derives the crisp outputs from vague inputs. It is in the form of A-> B ≡ if x is A, then y is B. The reasoner employs the forward chaining inference to check the rules, and the conclusion is added to the knowledge base when a new state is reached.

Some of the fuzzy rules applied for student fields 'age', 'phone_no', 'expertise' are given below:

person(?p), has_Age(?p,?age), greaterThanorEqual(?age,50)->Old(?p)
person(?p), has_Age(?p,?age), greaterThanorEqual(?age,40), lessThanOrEqual(?age,49)->Adult(?p)
person(?p), has_Age(?p,?age), greaterThanorEqual(?age,21)->lessThanOrEqual(?age,39)->Middle_Aged(?p)
person(?p), has_Age(?p,?age), greaterThanorEqual(?age,10)->lessThanOrEqual(?age,20)->Youngster(?p)
person(?p), has_PhoneNo(?p,?number), startsWith(?number,"9")->National_Phone_Number(?p)
person(?p), has_PhoneNo(?p,?number), startsWith(?number,"+")->International_Phone_Number(?p)
person(?p), has_Expertise(?p, "Business")->Business_Expertise(?p)
person(?p), has_Expertise(?p, "Marketing")->Marketing_Expertise(?p)

Some of the fuzzy rules applied for 'learning style' for the recommendation of learning content are given below:

person(?p), has_learningstyle(?p, ?perdimension),equals(?perdimension,"extremelysensitive" ^ "mediumsensitive") ->learning_content(?p, "Facts" & "Case_Studies")
person(?p), has_learningstyle(?p, ?perdimension),equals(?perdimension,"extremelyintuitive" ^ "mediumintuitive") ->learning_content(?p, "Theoretical")
person(?p), has_learningstyle(?p, ?inpdimension),equals(?inpdimension,"extremelyvisual") ->learning_content(?p, "Image" & "Diagram"& "Charts"& "Video")
person(?p), has_learningstyle(?p, ?inpdimension),equals(?inpdimension,"extremelyverbal") ->learning_content(?p, "Audio" & "Text")
person(?p), has_learningstyle(?p, ?prodimension),equals(?prodimension,"extremelyactive" ^ "mediumactive") ->learning_content(?p, "Example" & "PracticalExercise"& "Activity"& "Discussion" "& "Experimental" "& "ProblemSolving")
person(?p), has_learningstyle(?p, ?prodimension),equals(?prodimension,"extremelyreflective" ^ "mediumreflective") ->learning_content(?p, "Question" & "Examples"& "Links"& "Readings")

Some of the fuzzy rules applied for 'student interest' for the recommendation of learning content are given below:

person(?p), has_studentinterest(?p, ?sub),equals(?sub, "networking" & "data_communications") ->learning_content(?p, "Computer_Networks")
person(?p), has_studentinterest(?p, ?sub),equals(?sub, "ethical_hacking" & "network_security") ->learning_content(?p, "Hacking")
person(?p), has_studentinterest(?p, ?sub),equals(?sub, "app_development" & "mobile_development") ->learning_content(?p, "Mobile_Application_Development")
person(?p), has_studentinterest(?p, ?sub),equals(?sub, "multimedia" & "media") ->learning_content(?p, "multimedia")
person(?p), has_studentinterest(?p, ?sub),equals(?sub, "networking" & "network communication") ->learning_content(?p, "Data Communications")

From the above set of rules a conclusion for learning content is obtained based on student interest and learning style. Table 2. shows the sample result obtained from learning content recommendation using 'fuzzy IF THEN rules' based on learning style.

Table 2.Use of 'Fuzzy IF-THEN Rules

ID	DateofBirth	Nationality	Age Group	Learning Style			Types of Learning Content Recommended
				Processing	Perception	Input	
MCM12347CH	9/28/1988	Omani	Middle Aged	Neutral	Medium Intuitive	Neutral	Theoretical Text
MCM13219CH	11/12/1992	Omani	Middle Aged	Neutral	Medium Intuitive	Neutral	Theoretical Text
MCM12039CH	13/04/1990	Omani	Middle Aged	Medium Active	Neutral	Extremely Visual	Example, Practical Exercise, Discussion, Experimental, Problem Solving, Image, Diagram, Charts, Video
MCM13333CH	6/4/1989	Omani	Middle Aged	Medium Reflective	Neutral	Neutral	Question, Examples, Links, Readings
MCF12055CH	29/06/1991	Omani	Middle Aged	Neutral	Medium Intuitive	Extremely Visual	Theoretical Text, Image, Diagram, Charts, Video
MCM12031CH	20/03/1990	Omani	Middle Aged	Neutral	Medium Intuitive	NIL	Theoretical Text
MCF13184CH	26/12/1991	Omani	MiddleAged	Medium Reflective	Neutral	Neutral	Question, Examples, Links, Readings
MCM13281CH	8/22/1987	Omani	MiddleAged	Extremely Active	Neutral	Neutral	Example, Practical Exercise, Discussion, Experimental, Problem Solving

4.3. Evaluation

The main goal of the proposed system is to construct semantic student profile and to use it to predict learning preference of the students based on their learning interest and style. The knowledge base consists of a set of rules formed based on the student concepts of constructed ontology. Evaluation is done by testing the same set of students with the result of online survey questionnaire, where only knowledge about student interest and style is used. The questionnaire was attended by students belonging to different majors in computer science domain. Fig. 6.shows the graphical representation ofresults obtained during testing the rules on the students' data sets of proposed systemwith the results of manual system based on twometrics: accuracy and speed.

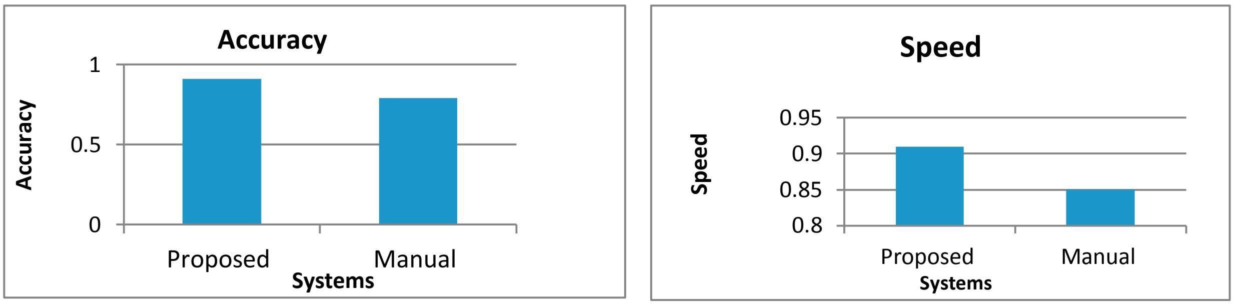

Fig. 6.comparison of proposed Vs manual systems

The overall accuracy of 91% is obtained on the basis of calculation using the formula in equation (3):

Accuracy = Correct Predictions / Total Number of Predictions (3)

The speed is obtained by the total percentage of time required to get the result from both the systems. By analysing the results, it is foundthat the proposed system is able to predict the student preference with good accuracy and speed compared to manual systems. The experimental results proved that the proposed dynamic semantic student profile is able to classify, retrieve and predict the learning preferenceaccurately; particularly on student interest and learning style and this can be successfully applied in learning to provide maximum requirements to the students. The result would help the educators to analyse the performance of the students behaviour using the learning system and also to frame the course materials based on the preferences of the students.

5. Conclusions

The paper proposes an approach to construct ontologybased semantic student profile for a learning system. The construction of student profile is achieved using ontology and the automatic updating of ontology is doneusing WordNet to incorporate the dynamic characteristics of the student, particularly the student interest and learning style. To get semantic retrieval from constructed ontology, fuzzy concepts are integrated with ontology in the form of fuzzy linguistic variable and 'fuzzy IF THEN rules'.The fuzzy linguistic variables are used for the precise representation of existing ontology concept in order to make more specific and precise classification and semantic retrieval of information. The predictive student model is generated through the implementation of 'fuzzy IF THEN'rules based reasoning concept,to predict the learning preference of new students. The conducted experiments have shown the successful completion of student profile generation, updating, fuzzy semantic retrieval and prediction of student information.

References

[1] Boyce and PahlC. (2007) "Developing Domain Ontologies for Course Content the Development of Ontologies."*Educational Technology & Society*, **10(3)**:275-288.

[2] D. Trong, N Mohammed, L. Delong, and J. Geun. (2009) "A Collaborative Ontology-Based User Profiles System," *ICCCI 2009*, *Springer-Verlag Berlin Heidelberg LNAI* 5796, 540–552.

[3] Ferreirs-Satler. M, Romero. F.P., Menendez-Dominguez. V.H, Zapata. A and Prieto. M.E. (2012) "Fuzzy ontologies-based user profiles applied to enhance e-learning activities." *Soft Computing*, **16(7)**:1129-1141.

[4] Fernando Bobilloaand Umberto Straccia. (2016) "The fuzzy ontology reasoner FuzzyDL."*Knowledge-Based Systems*, vol. 95, 12-34.

[5] Jun Zhai, Jianfeng Li and Yan Lin. (2011) "Semantic Retrieval Based on SPARQL and Fuzzy Ontology for Electronic Commerce."*Journal of Computers*, **6(10)**:2127-2134.

[6] Jun Zhai, Yan Chen, Yi Yu, Yiduo Liang and Jiatao Jiang. (2009) "Fuzzy Semantic Retrieval for Traffic Information Based on Fuzzy Ontology and RDF on the Semantic Web.*" Journal of Software*, **4(7)**:758-765.

[7] J. Zhai, Y. Cao and Y. Chen. (2008) "Semantic information retrieval based on fuzzy ontology for Intelligent Transportation Systems."*in: Proceedings of the 2008IEEE International Conference on Systems, Man, and Cybernetics, Singapore*, 2321-2326.

[8] J. Zhai, J. F. Li, and Y. Chen. (2010) "Knowledge modeling of product data based on fuzzy ontology."*Applied Mechanics and Materials*, vol. 26-28, 347-351.

[9] Khaled M. Fouad, Mofreh A. Hogo, ShehabGamalel-Din and Nagdy M. (2010) "Adaptive E-Learning System based on Semantic Web and Fuzzy Clustering."*International Journal of Computer Science and Information Security*, **8(9)**: 308-315.

[10] KishorWagh and Satish Kolhe. (2011) "Information Retrieval Based on Semantic Similarity Using Information Content."*IJCSI International Journal of Computer Science Issues*, **8(4)**:1694-0814.

[11] LinglingMeng, Runqing Huang and JunzhongGu. (2013) "A Review of Semantic Similarity Measures in WordNet."*International Journal of Hybrid Information Technology*, **6(1)**:1-12.

[12] Lixin Han, Guihai Chen. (2009) "A Fuzzy Clustering Method of Construction of Ontology-based User Profiles." *Advances in Engineering Software*, **40(7):**535-540.

[13] Marek Reformat and Sayed KooshaGolmohammadi. (2009) "Updating User Profile using Ontology-based Semantic Similarity."*FUZZ-IEEE*, 20-24.

[14] Mateus Ferreira-Satler, Francisco P. Romero, Victor H. Menendez, Alfredo Zapata and Manuel E. Prieto. (2010) "A Fuzzy Ontology Approach to represent User Profiles in E-Learning Environments." *In: Proceedings of IEEE International Conference on Fuzzy Systems* (FUZZ), 1-8.

[15] Mariangela Biasiotti, Enrico Francesconi, Monica Palmirani, Giovanni Sartor and Fabio Vitali.(2008)"Legal Informatics and Management of Legislative Documents."*Global Centre for ICT in Parliament Working Paper*, No.2:62-76.

[16] T. Sheeba, Dr. Reshmy Krishnan. (2015) "Semantic retrieval based on SPARQL and SWRL for learner profile." *International Journal of Applied Engineering Research*, ISSN 0973-4562, **10(14):** 34549-34554.