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Fuzzy Integrated Ontology Model of Dynamic Learner Profiling

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Abstract: ***In the context of lifelong learning, learner profile has emerged as a feasible model that support and promote the provision of lifelong learning opportunities. Learner profile describes the attributes and outcomes of education in a learning system. It includes information on learner's gender, skills, education, interest, learning preferences, learning style, etc. This paper proposes an approach to construct a fuzzy based semantic learner profile in the promising technology of semantic web by using the concept of ontology and use it for the reasoning of learner preferences. The approach starts with the collection of learner's static and dynamic data. The dynamic data of learner particularly learner interest and learning style are extracted by weblog analysis and using algorithms such as semantic based representation using WordNet and modified decision tree classifier with strong rules based on Felder-Silverman learning style model. The retrieved data is then used to construct learner profile using ontology in which automatic learner profile updating is obtained using ontology based semantic similarity algorithm. Finally to achieve semantic retrieval from learner profile ontology, fuzzy concepts such as fuzzy linguistic variable and fuzzy IF THEN rules are applied. Fuzzy linguistic variable facilitate semantic retrieval and more specific classification from learner profile ontology and fuzzy IF THEN rules predict the learning preference of new students based on the forward chaining reasoning process implemented in the existing ontology model. The final representation of semantic fuzzy ontology based learner profile improves the performance of tasks such as classification, semantic retrieval and prediction of learning preference to the new learners. The case study is conducted for the real-time learners involved in studying the courses registered in Moodle Learning Management System. The experiments were performed with NetBeans IDE, Jena framework and Protégé 4.2 beta editor. The experiments confirm that the proposed learner profile is a good representation of the learner's preferences.***

Keywords: ***Decision Tree, Fuzzy, Learner Profile, Learning Management System, Ontology, Reasoning, Semantic Web, WordNet.***

I. INTRODUCTION

Nowadays, most of the universities all over the world are widely using online learning systems for education.

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The major challenge faced in these systems is that the learners are treated in the same way as the system does not know anything about the learners using the system. Also, more time is spent by the learners to find the learning contents suitable to their needs.

To satisfy the learning needs of diverse learner's and to retrieve learning contents relevant to the learner's needs and requirements, a learner profile is profoundly necessary to reflect the diverse needs of the learner. A learner profile [1] represents a structure that contains information concerning the learners' background, interest, and preferences, etc. It forms the most suitable and good representation of learner's requirements which enhance the usage of learning content. One of the main aims of this paper is to explore the development of learner profile in the promising technology of semantic web and use it for the prediction of learner preferences. The semantic web technology depends on ontologies as a tool to model an abstract view of data for the purpose of transportable and comprehensive machine understanding. The ontology-based learner profile representation would improve the performance of different tasks such as information filtering, classification, etc.

However, the conceptual formalism supported by typical ontologies may not be sufficient to represent imprecise and uncertain information. The possible solution is to integrate fuzzy concepts in existing ontology in order to help users for making decisions on learner preference in a more precise way. This paper aims a new approach to improve the learner profile representation and use it for the learner preference. To do so, learners data (static and dynamic) are collected along with the WordNet semantic representation of learner interest; decision tree classifier for learning style based on FSLSM (Felder Silverman Learning Style Model); learner profile construction using ontology; automatic ontology updating and using fuzzy concepts, a combination of that, can suitably represent learner profile to consistently reflect both implicit and explicit learners details.

II. BACKGROUND

There are several works proposing user profile construction in different areas. An ontology-based user profile model [2] is created based on the static profile properties of each individual user and demonstrated in two different applications of personal information management and adaptive visualization. The drawback of this model is that it does not include the dynamic and temporal characteristics of a learner. A new concept of ontology-based semantic similarity method [3] is proposed for automatic learning and updating of the user profile in a 'music' domain.

The updating is done by comparing the similarity between user's profile items and new items using an importance measure combined with ontology-based semantic measure in order to add the most relevant items to the user profile. A fuzzy ontology [1] representing user's preference and interests from learning objects is constructed automatically in AGORA e-learning platform using related degree of user-relevant terms, and updating is done when new interesting documents are created or selected by users. An ontology-based user profile (FCOU) [4] is created using fuzzy clustering techniques with an augmented Lagrangian function and some optimization techniques. The final result clusters the users' information in various user profiles simultaneously with different accuracy level. A user profile [5] is developed using information from different search spaces of users such as blog, organizational sites, personal webpage, and other sites. An initial profile is created by the user's documents and then features from these documents are extracted using WordNet and using Lexico-Syntactic pattern for hyponyms methods. The similarity score is calculated among set of users with similar interest using collaborative user methods and the profile is also learned with other similar users using an ontology matching approach.

The various works proposed in the area of 'Fuzzy Logic' is reported in this section. Semantic retrieval [6] [7] from the ontology is done on semantic web by exploring the concept of 'fuzzy linguistic variable' for classification and applied successfully in both areas of 'electronic commerce' and 'traffic information service'. The concept of fuzzy linguistic variables is applied to Resource Description Framework (RDF) data model and SPARQL query language is constructed between fuzzy concepts for semantic query expansion. The exploration of how fuzzy logic and ontologies could facilitate the exploitation and mobilization of tacit knowledge and imprecise data in organizational and operational decision making is explained [8]. An efficient and accurate diet recommendation method [9] is proposed based on person Prakriti and current season. Ontology integrated with fuzzy logic is used to represent the food knowledge collected from different dietician's plans for different Prakriti. Type-2 Fuzzy Logic is used to handle the uncertainty information that comes from different dieticians. A fuzzy ontology representation [10] for user knowledge is proposed, in which the information is initially retrieved using Group Decision Making (GDM) process which represents information by the user's majority, and then the retrieved information is stored in an organized way using a fuzzy ontology. The final representation provides a mathematical environment to perform queries on stored data and also to consult and benefit from the retrieved information. A novel fuzzy user-oriented cloud service selection system (Cloud-FuSeR) [11] is proposed which help users to choose right cloud services using multi-criteria decision-making technique. For service matching, a fuzzy ontology is built to model uncertain relationships between the objects that exist in databases, and semantic similarity between concepts is calculated using a novel analytic hierarchy process.

Even many researchers focus on a different concept of building user profiling, there is a lack of complete learner profile in the existing research works with full learner details and its usage in the learning system of Moodle. However, making the approach applicable to Moodle LMS (Learning Management System) is challenging than developing it in general. It requires specific consideration on supporting the different features and services of LMS. Hence the proposed approach is to develop a fuzzy ontology-based dynamic learner profile that captures the complete details of the learner supporting semantic web technology with fuzzy concepts in order to satisfy the learning requirements in an efficient way.

The rest of the paper is structured as follows: Section 3 describes the methodology used; Section 4 presents the experimental results and discussion; Section 5 gives the conclusion and finally references.

III. METHODOLOGY

The proposed approach is to develop a fuzzy ontology-based semantic dynamic learner profile based on the learner's individual differences and use it for the prediction of learner preferences. The overview of the proposed system architecture is shown in Fig. 2.

A. Phase 1- Data Collection

The process of constructing a learner profile starts with the collection of data. There are mainly two types of data available for a learner, static and dynamic. Static data is fixed data set that does not change and is collected from the database management software of institution, while the dynamic data (particularly learner interest and learning style) may change after updating and has to be continually updated. It is extracted from the weblog files created in the 'Moodle' LMS of institution while learner is using the system.

B. Phase 2- Data Preprocessing

The weblog files are pre-processed to extract the learner interest and learning style of each learner.

Learner Interest Retrieval. The learner interest retrieval is achieved by processing the weblog files representing the frequently accessed documents of each learner. The method uses the concept of WordNet to represent the documents in a semantic way. The overview of the proposed method is shown in Fig .1.

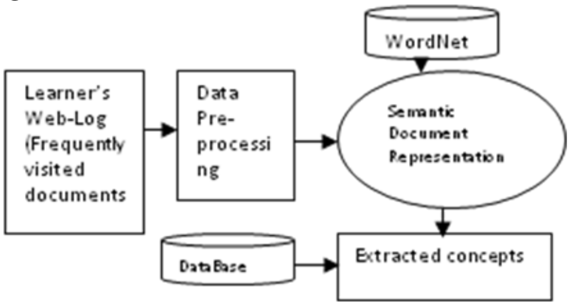

Fig. 1. Architecture of Extracting Learner Interest.

The initial step is an extraction of documents for each learner from the weblog files created during access of LMS based on the number of times each document has been visited. The documents are downloaded and then preprocessed to remove unwanted words using stop words elimination and stemming method [12]. From the preprocessed documents, a bag of words representing each document is done using the standard VSM (Vector Space Model).

Once the words are identified, the relevance to learner interests is evaluated using the 'WordNet' concept which enhances document representation by improving the semantic relationship between words. WordNet returns an ordered list of synsets when applying to a set of words in the document. To evaluate and select the most relevant

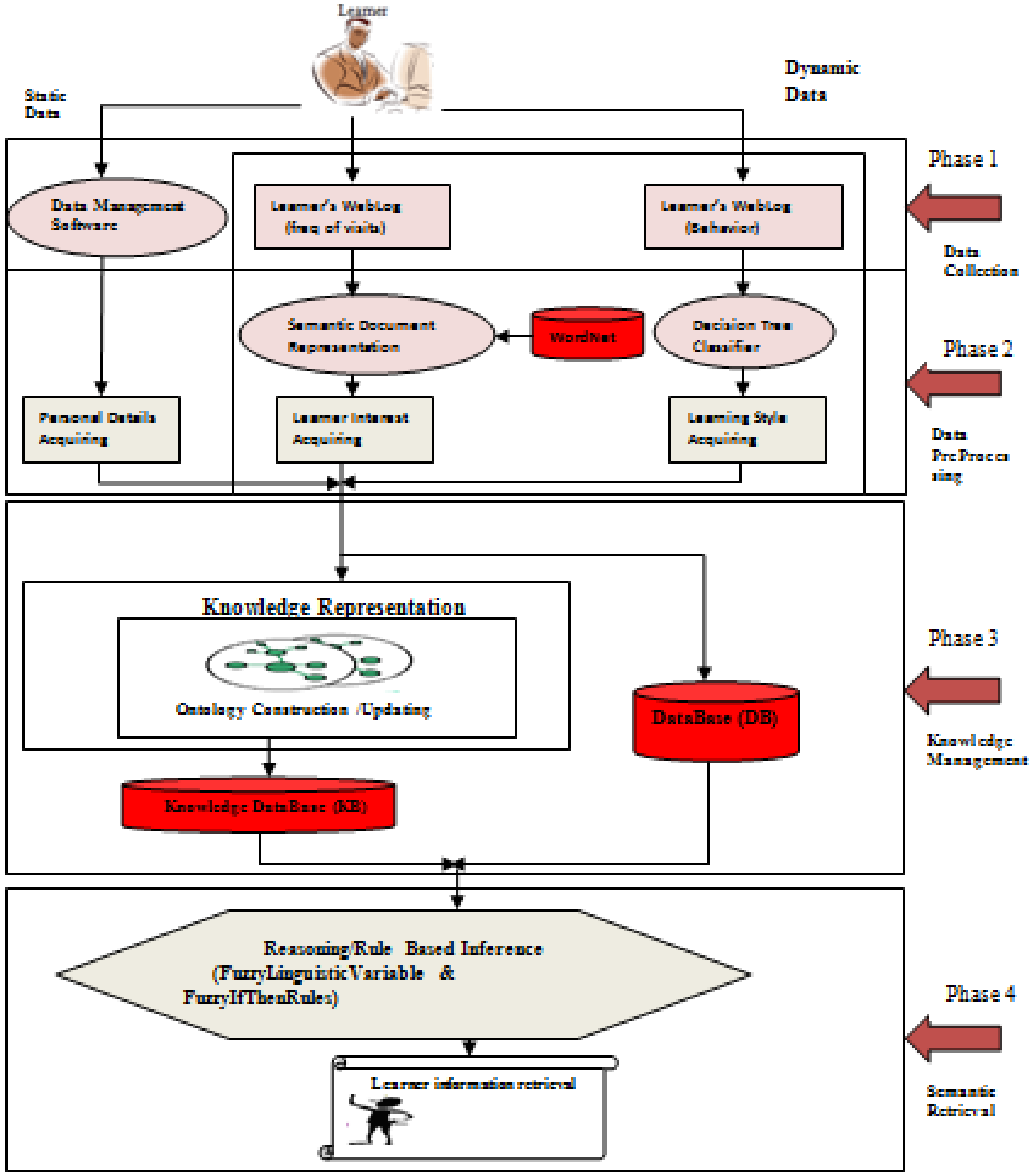

Fig. 2. System Architecture of Proposed

Approach.

items from the set of synsets, WSD (Word Sense Disambiguation) algorithm is used which estimate the semantic similarity based on Lin's method for each pair of words.The similarity with the highest score expresses the relevant similarity of terms that can be added to the profile. The last step is identifying other relevant relationship like hypernyms and hyponyms from the WordNet database for the selected words. Hypernyms represents broader meaning of concepts and hyponym represents a more specific meaning of concepts. The proposed algorithm for extracting learner interest is shown in Fig. 3

Algorithm
Input: Weblog files of each learner
Output: Concepts representing learner interest

1. Access the 'information' field of web log files of each learner.
2. Download the document visited more than twice.
3. Preprocess documents
4. Remove stop words, extra spaces, punctuation symbols, numbers etc.

5. Apply standard Porter Stemming Algorithm to transform words into their stem.
6. Apply keyword extraction method using TF-IDF method to find the importance of a word is to a document.
a. Construct a document term matrix

a. Compute normalized term frequency (TF)

TF(w) = (No of times word w appears in a document) / (Total no of words in the document)

b. Calculate Inverse Document Frequency (IDF)

IDF(w)=log_e(Total no of documents/No of documents with word w in it)

c. Calculate TF-IDF weight of words in the selected document W

W (w) = TF (w) * IDF (w).

d. Select top high-weighted words which are above threshold value (n% terms from each document according to tf- idf value). Look up WordNet to find the semantic relationship of target keywords

a. Let $D_n = \{C_1, C_2, \ldots\ldots, C_m\}$ be the set of selected concepts from document D_n.

b. For each selected concepts in document do

c. Obtain the synsets S_i: $S_i = \{S_{1i}, S_{2i}, \ldots.., S_{ni}\}$ in the hierarchy, such that concept C_i has $|S_i|$=n senses from WordNet.

d. Mark Si

e. To select the best sense of each extracted concept from document D_n Word Sense Disambiguation (WSD) algorithm based on semantic similarity method of Lin's method is applied.

i. For each synsets in the hierarchy do

ii. Find similarity between two concepts c1 and c2 using the formula:

$sim_{lin} = 2*IC(lcs(c1,c2)) / IC(c1)+IC(c2)$

where IC is the information content of the concept and lcs(c1, c2) is the lowest common subsumer of concepts c1and c2.

iii. The words are ordered based on the similarity score.

iv. The words with highest similarity score are taken as the final sense.

v. Insert the sense into the database.

2. Look up WordNet to find the Hypernyms and Hyponyms: Obtain the hypernym and hyponyms for the selected sense in the previous step and insert them into the database.

Hypernyms of concepts represent broad concepts up to a certain level of generality $Hf_e = \sum_{b \in H(c,r)} Cf_b$

Hyponym of concepts represents specific concepts from the level of generality. $Hf_o = \sum_{b \in H(c,r)} Cf_b$

where H(c,r) is the set of concepts C_H

Fig. 3. Algorithm of Extracting Learner Interest.

Learning Style Retrieval. The learning style of a learner is processed from the various actions performed by the learner while using the LMS. The proposed architecture is shown in Fig. 4.

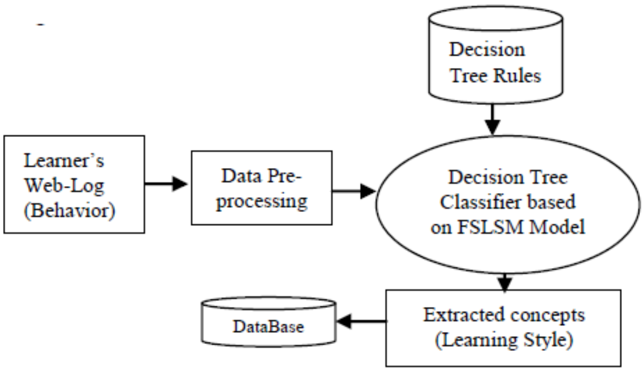

Fig. 4. Architecture of Extracting Learning Style.

The weblog files of each learner collected from LMS records the learners' behavior and the participation in using the course-related tools such as live chat, forum discussion, quizzes and class assignments. These files are preprocessed to extract the actions and details about the actions such as how much time spent on exams, how many times exams are revised, etc. The overall time a learner spent on actions like exams, assignments, etc. are then calculated and then used to construct the decision tree where the dataset is recursively divided into smaller subsets until all the data in the division have the same class. Decision tree classifier is chosen as it is easy to use and the rules of the classification are also easy to understand and visible. The rules play a vital role to reflect each learner's learning style behavior patterns of FSLSM and are used to predict the learning style of new learners. The rules used are more significant to classify and predict the learning style of each learner more precisely and accurately based on FSLSM.

Fig. 5 shows the modeling of decision tree generated by the algorithm (Fig. 6) from the training samples based on FSLSM. The decision tree has a tree-like structure where leaves represent class labels, internal nodes denote a test on an attribute and branches represent an outcome of the test that leads to those class labels.

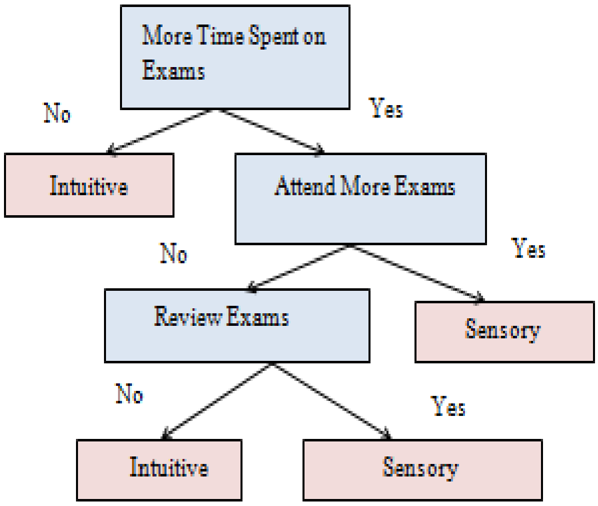

Fig. 5. An Example of Decision Tree Model.

Algorithm

Input: Weblog files of each learner

Output: Learning style of each learner in 3 dimensions of FSLSM

1. Access the weblog files of each learner.
2. Preprocess weblog files
   Filter the activities and their corresponding actions of each learner from weblog files based on the three dimensions of FSLSM model.
3. Create a learning style model
   a. Determine the activities of learners in Moodle LMS
   b. Build Tree using decision tree classifier
      i. Initially, Tree T is empty
      ii. T = Create the root node and its splitting attribute
      iii. T = Add branch to the root node for each split attribute and label it with test value
         For each branch do
         Move to the split attribute
         Test on the possible value of split attribute
         Create a new branch below root based on the test result
         If stopping point is reached for this branch, create leaf a node with the appropriate label.
4. Predict the learning style model
   a. Input is the learner activities
   b. Start at the root node
   c. Move to the decision node
   d. Test on each possible value of the decision node and descend the appropriate branch
   e. Test repeated until a leaf node is reached
   f. Return the classification of leaf node which is the learning style.

Fig. 6. Algorithm of Extracting Learning Style.

C. Phase 3- Knowledge Management

Learner Profile Construction. The approach to construct learner profile is based on the concept of ontology. The ontology describes the basic terms and their relations comprising the vocabulary of a domain as well as the axioms that constrain the interpretation among terms. The ontology construction process mainly comprises of four main steps i.e. defining important concepts and its terms, defining concepts, relation of concepts and individuals, implement and evaluate ontology to check for accuracy. OWL (Web Ontology Language) is the language designed mainly for ontology development. The OWL [13] ontologies are processed using Java and using Jena framework the processed ontology is stored in OWL file. The OWL [14] file is then viewed using the ontology editors. The proposed system uses protégé as the editor as it is a free and open-source editor for building, manipulating and managing the ontologies.

Learner Profile Updating. The automatic updating of new concept into the existing learner profile ontology is done using the proposed method of ontology-based semantic similarity measures using WordNet. The algorithm is illustrated in Fig. 7. The method starts with detecting any changes in the learner profile information stored in the database. That change is updated by first finding the new concept c1 most similar to the concept c2 in existing ontology using the information content semantic similarity measure given in (1):

$$res(c1,c2) = IC(LCS(c1,c2)) \quad (1)$$

The result returns a numeric score which represents the degree to which both concepts are similar or not. The concept with high similarity score is taken and then the position is determined by finding the depth between the two concepts to know if: new concept c1 is the ancestor of c2 in ontology; new concept c1 is descendant of c2 in ontology; c1 and c2 are at the same level in ontology. The return is an integer value. Based on the return value, the concepts are added to the learner profile. If the returned value is positive then c1 is the son of c2 in ontology; equal to 0 then c1 and c2 are brothers in ontology; negative then c1 is the father of c2 in ontology.

Algorithm

Input: Term to be updated

Output: Term updated in learner profile ontology based on the similarity score

1. Get the term to be updated in learner 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 position in learner profile ontology by finding the difference of depth between two concepts. The return value is an integer.
   a. If the value >0 then c1 is the ancestor of c2 in ontology
   b. If the value =0 then c1 and c2 brothers in ontology
   c. If the value<0 then c1 is the descendant of c2 in ontology.

Fig. 7. Algorithm of Learner Profile Updating.

D. Phase 4- Semantic Retrieval

To handle the uncertain information represented in learner profile ontology and to perform reasoning for making decisions on learner preference, fuzzy logic is applied to the ontology in the form of ‘fuzzy linguistic variable’ and ‘fuzzy IF-THEN rule’.

Fuzzy linguistic variable is used to make distinction on the vague knowledge representation of existing concepts of learner profile ontology. The definition of fuzzy linguistic variable [6] is given as a 4-tuple (X, T, M, U), where: X is the name of fuzzy linguistic variable; T is the set of terms which is the value of fuzzy linguistic variable; M is the mapping rules which map every term of T to fuzzy set at U; U is the universe of discourse. Initially the crisp values of learner profile concepts are used to create a fuzzy set which includes linguistic variables of each concept.

A fuzzy set is defined mathematically by assigning a value from universe of discourse representing degree of membership in the fuzzy set. The values assigned fall within a specified range in the unit interval [0, 1].

Fuzzy IF-THEN rules are used to formulate reasoning and generate decisions on the learner preference under specific rules, particularly on learner interest and learning style. It identifies the inputs and outputs of a system and transforms the vague inputs into crisp outputs. It is in the form of A-> B ≡ if x is A, then y is B. Reasoning [13] plays a significant role in the knowledge-based implementation systems. There are two reasoning strategies: forward chaining and backward chaining. The forward-chaining starts with all the known facts and tries to use rules to find the desired conclusion. The backward chaining works backward to find supporting facts from the desired conclusion. The proposed system uses forward chaining inference engine to search the rules in knowledge base with the initial facts for a match in order to make desired decisions on learning preference based on learner interest and learning style.

IV. RESULTS AND DISCUSSION

For experiments, the LMS Moodle has been used to do the experiment on estimating learner interest and learning styles of the learners. An example of real-life web log files of approximately around 300 learners used during 3 semesters (i.e. over a period of one year) for 5 different online courses in the computing department is used. The initial profile which defines the static characteristics is obtained from the institution data management software. The weblog files define the usage of the learning system in the form of a table (Fig. 8) in which each entry corresponds to 'date and time of access', 'IP address', 'full name', 'actions' and the 'information of action done'.

Time	IP address	User full name	Action	Information
Tue 3 March 2015, 8:23 AM	192.168.200.2	Ayman Al-hashmei	course view section	Outcome 3
Tue 3 March 2015, 8:22 AM	192.168.200.2	Hilal Alqurri	course view	Network Technology and Data Communications (New)
Tue 3 March 2015, 8:07 AM	192.168.200.2	Hilal Alqurri	resource view	L3-PTO Switched Services
Tue 3 March 2015, 8:07 AM	192.168.200.2	Hilal Alqurri	course view section	Outcome 3
Tue 3 March 2015, 8:07 AM	192.168.200.2	Hilal Alqurri	assign view	View own submission status page.
Tue 3 March 2015, 8:04 AM	192.168.200.2	Rashad Albalushi	assign submit	Submission status: Submitted for grading. The number of file(s) : 1 file(s).
Tue 3 March 2015, 8:04 AM	192.168.200.2	Rashad Albalushi	assign submit	Submission status: Submitted for grading. The number of file(s) : 1 file(s).
Tue 3 March 2015, 8:03 AM	192.168.200.2	Rashad Albalushi	assign submit	Submission status: Submitted for grading. The number of file(s) : 1 file(s).
Tue 3 March 2015, 8:02 AM	192.168.200.2	Rashad Albalushi	assign view submit assignment form	View own submit assignment page.
Tue 3 March 2015, 8:02 AM	192.168.200.2	Rashad Albalushi	assign view	View own submission status page.
Tue 3 March 2015, 8:02 AM	192.168.200.2	Hilal Alqurri	course view section	Outcome 3
Tue 3 March 2015, 8:01 AM	192.168.200.2	Ayman Al-hashmei	course view section	Outcome 3

Fig. 8. Sample WebLog File.

A. Learner Interest

The 'documents' and 'number of times the documents visited' during different sessions of around 300 learners are retrieved from the 'information' field of each weblog files. The document types are in the form of text, powerpoint, and hyperlinks. A collection of around 100 documents concerning from 5 predefined computer science topics are used. Each topic includes around 20 documents. All these documents are preprocessed using stop word elimination and stemming method and the bag of words is extracted from these documents using standard VSM. In the final stage, the bags of words are represented using semantic concepts and relations (Table-I).

Table- I: Sample Document Representation

Document	Document Items Using VSM	Semantic Representation using WordNet	Word with High Similarity Score
Doc 1…..	Network / Topology/ Equipment	Web/Broadcasting/Mesh, meshing, meshwork Place/ regional anatomy/ analysis situs/ Network topology Instrumentality, Instrumentation.	Broadcasting Network Topology Instrumentation
Doc 2	Wireless/ Interface/ Device	Radio Communication/Medium/ Transmission/ Receiver Chemistry/ User interface/Port Instrumentality, instrumentation	Radio Communication Port Instrumentation
Doc 3	Multiplex/ Network	telecommunication, telecom Web/Broadcasting/Mesh, meshing, meshwork	Telecommunication Broadcasting
Doc 4	data/ data structure	Information Data structure	Information Data structure
Doc 5	Media/ Graphics	Medium art work/ art	Medium art
Doc 6	Language / Program	Linguistic communication/ speech/programming language Programme	programming language Programme

For evaluation, the documents semantic indexing method is compared with the results returned using classical keyword indexing (VSM) method. For both the methods, the following quantities: precision and recall have been computed using equation (2) & (3):

$$\text{Precision} = \frac{\text{No. of relevant document retrieved}}{\text{Total number of documents retrieved}} \tag{2}$$

$$\text{Recall} = \frac{\text{No. of relevant document retrieved}}{\text{Total number of relevant documents}} \tag{3}$$

The graph drawn for the precision and recall values of both methods (Fig. 9 and 10) indicates that both values are increased for semantic-based representation compared to the term based representation.

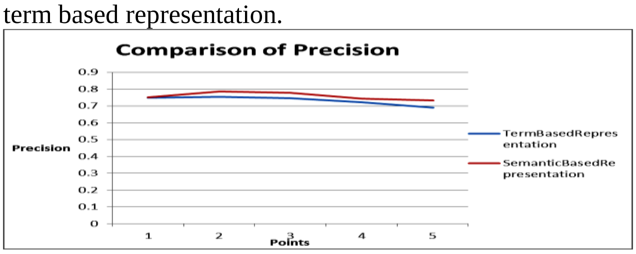

Fig. 9. Comparison of Precision of TF-IDF Vs WordNet.

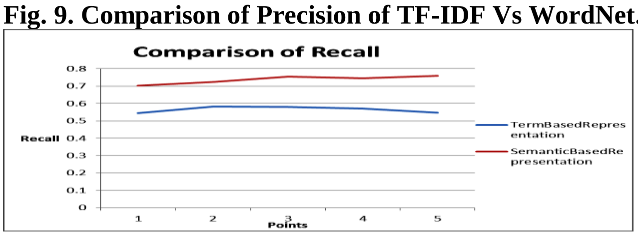

Fig. 10. Comparison of Recall of TF-IDF Vs WordNet.

Evaluation is also done by calculating the overall classification accuracy obtained for both the methods using the formula in (4):

$$\text{ClassificationAccuracy} = \frac{\text{No of documents correctly classified}}{\text{Total No of documents}} \tag{4}$$

The graph in Fig. 11. shows that, with a training sample of 16 - 96 documents, the performance of classification obtained using semantic-based representation using WordNet, is much better than that obtained using term-based representation. The overall classification accuracy obtained is 81%.

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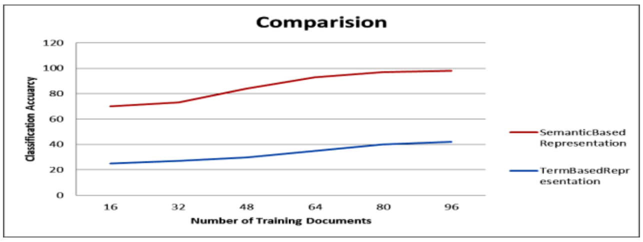


Fig. 11. Classification Accuracy.

The reason is that in term-based representation, the words per topic is very small, whereas, in WordNet-based representation, the words per topic is expanded in a weighted manner. As a result, with a term-based representation for a document, a document has given a low similarity measure with documents from the same topic since they have only a few in common words. With WordNet representation for a document, a document has given a high similarity measure with documents from the same topic, since the words have expanded using WordNet. Hence, the results obtained in the experiments suggest that the integration of WordNet has improved the classification results.

B. Learning Style

In LMS, the courses are represented in different activities such as notes, power points, hyperlinks, assignments, quizzes, etc. The weblog files record the activities and the actions performed on these activities (Table-II) such as type of learning content preferred (notes, powerpoint, hyperlinks), the number of assignments done, the number of quizzes attended with the number of revisions and delivery time, participation in discussion forums and chat facilities, etc. Initially, these activities and actions are first filtered out from web log files for each learner.

Table- II: Activites Vs Actions of WebLog Files.

Activities	Actions
Quiz	quiz attempt, quiz continue attempt, quiz close attempt, quiz review, quiz delivery time, quiz done
Assignments	assign view, assign submit, assign view submit assignment form
Chats	chat view, chat report, chat talk, chat add
Forums	view forum, view discussion, add discussion, add post
Notes	resource view
Power points	resource view
Hyperlinks	url view

The classification is done by dividing the entire dataset of 300 learners into 2 sets, based on the split of 210 learners (70%) for training and 90 learners (30%) for testing. The selected 210 training samples are classified using decision tree classifier and then the remaining 90 testing samples are used to observe the performance evaluation.

Performance Evaluation:

Comparison with ILS (Index of Learning Styles) Questionnaire: Evaluation is done by testing the same group of learners with the result of ILS questionnaire. The questionnaires were subsequently distributed to learners and were asked to fill up the questionnaire. A total of 200 usable questionnaires were selected as they were properly filled by the learners. The comparison is done by calculating classification accuracy on the 3 dimensions of FSLSM as per (5) and the results are shown in Table-III.

Accuracy = Correct Predictions / Total Predictions
Error Rate = Wrong Predictions / Total Predictions (5)

Table -III. Experimental Results of Decision Tree Classifier Vs ILS Questionnaire.

Performance	Processing	Perception	Input	Overall
Classification Accuracy	86%	95%	90%	90%
Error Rate	14%	5%	10%	10%

The perception dimension has a high accuracy of 95% as most learners are interested in doing exams and exercises in the course and hence variance is less. The input dimension has an accuracy of 90% since most of the learners prefer to use powerpoint slides and hyperlinks for their study rather than theoretical notes which lead to less variance. The processing dimension has an accuracy of 86% as the learners are interested in the usage of forums and chats facilities whereas the usage in LMS is less and hence variance is found in this dimension. The overall achieved results range from 86% to 95% which shows high accuracy for the proposed classifier, thereby proving its suitability for identifying the learning style of learners with an average accuracy of 90% and a very less error rate of 10%.

Comparison with other Standard Classifiers: The performance of the proposed classifier is evaluated with other standard classifiers using the software weka (Waikato environment for knowledge analysis) based on the performance done by classification accuracy used in equation (4). Fig. 12 shows a high percentage of accuracy compared with various classifiers in all the 3 dimensions of FSLSM.

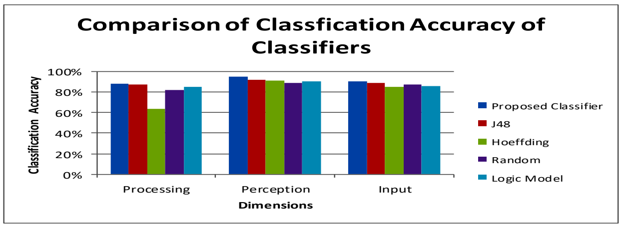


Fig. 12. Comparison of Classification Accuracy for FSLSM Dimensions.

The decision tree classifier with the set of significant rules makes it possible to detect the learning styles of new learners based on their behavior patterns.

C. Semantic Learner Profile Construction

The learner profile is constructed using the retrieved information stored in the database. The source code in Java read the input learner profile information and create the ontology domain with the student as the main class and attributes of a student such as a name, date of birth, date of birth, nationality, email, learner interest and learning style as subclass as indicated in Fig. 13. Jena APIs are used to store four main elements of ontology such as classes, object properties, data properties and named individuals (Fig. 14) in the OWL file. The obtained OWL ontology is then successfully loaded on a Protégé Editor as shown in Fig. 13.

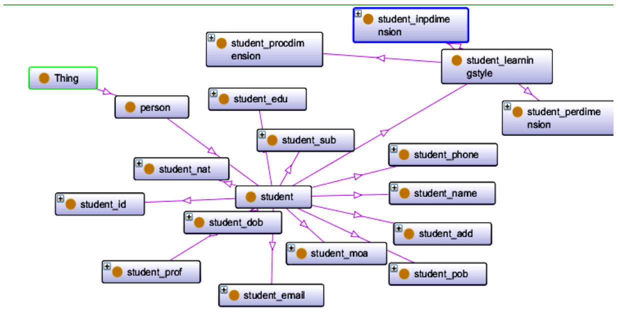


Fig. 13. OntoGraf View of Ontology in Protégé 4.2 beta.

Classes: denote a set of learner profile concepts. Example: name, education, email, nationality, learning style, interest, etc.

Properties: describes the relation between classes and objects. Each property has a domain and range.

Object Property: links two classes. Example: <has profession>, <has education>.

Data Property: links classes and primitive data type. Example: <has email>

Named Individuals: represents the instance of the concept/class. It takes the values of classes such as name, email, date of birth, interest, etc. from the database.

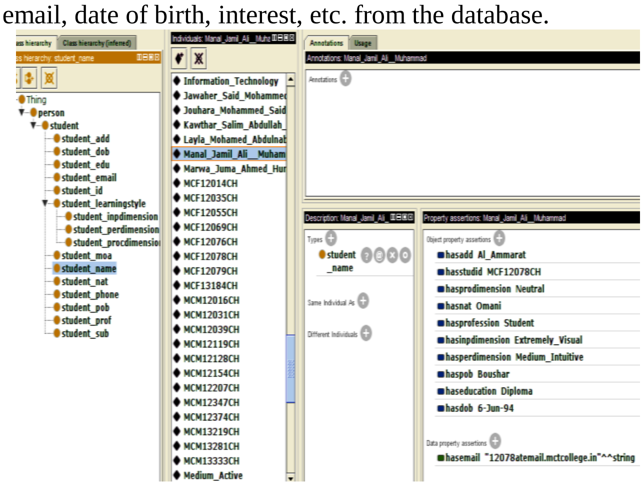


Fig. 14. Four component of Ontology.

D. Learner Profile Updating

WordNet-based similarity method is used to evaluate the similarity between the new concept and all the concepts in the learner profile ontology. WordNet is used as a basic ontology. Table -IV presents the similarity score obtained with the new concept "Masters" and the existing concepts of learner profile ontology.

Table-IV. Similarity score obtained between "Masters" and Learner profile terms.

Student profile terms	Semantic Similarity Score (res)	Position	Relation between two concepts
person	1.9033		
student	1.9033		
id	0		
name	0		
Mode	0		
DOB	0		
Email	0		
Phone No	0		
Education	0		
Profession	0		
Address	1.1692		
Place of Birth	1.1692		
Nationality	0		
Learning Style	0		
Learner Interest	0		
Bachelor degree	5.4219		
Diplomate	6.1028	-3	'Masters' added with Diplomate'

In Table-IV, the concept "Diplomate" and "Masters" gain a high similarity score compared to the other concepts. Hence, the position of "Masters" relative to "Diplomate" in WordNet is evaluated and zero value (depth (Masters) depth (Diplomate) = 15 – 15 = 0) is obtained. Therefore, "Masters" are added with "Diplomate" as shown in Fig. 15.

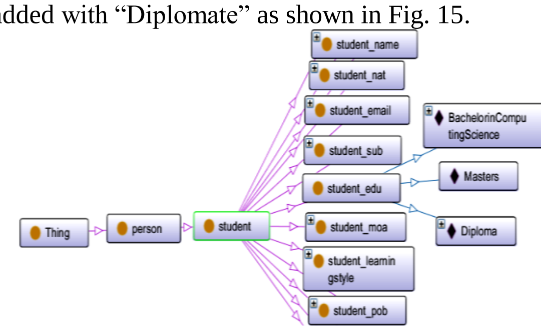


Fig. 15.Existing Learner Profile Ontology after adding "Masters"

E. Semantic Retrieval

The fuzzy logic approach is used for the precise representation and for reasoning the learner preference by using the concept of 'fuzzy linguistic variable' and 'fuzzy IF-THEN rules'.

Initially, the crisp concepts of learner profile ontology such as name, nationality, date of birth, interest, education, learning style, profession, etc. are converted into fuzzy values by assigning values of multiple linguistic variables. The Table-V shows some of the main fuzzy linguistic variables and values used in learner profile ontology based on the following classifications:

Age = {0-15, 16-24, 25-30, 31- 40, 41-50, 51-60, >=61}

Profession = {student, labour, sales executive, commander, engineer, manager}

Education = {no education, elementary school, high school, diploma, bachelor's degree, master's degree, doctoral degree}

Table-V. Linguistic Variables.

Learner Profile concepts	Linguistic Variables
age	very young, youngster, middle-aged, mid-life, adult, old, very old
profession	no profession, very low profession, low profession, medium profession, high profession, very high profession
education	not educated, very little educated, little educated, educated, medium educated, highly educated, very highly educated

The values of membership function are then assigned to each element of the linguistic variable defined by fuzzy set on universe of discourse. For example, a fuzzy set representing the concept of education assign a degree of membership of 0.1 to 'not educated', 0.3 to 'very little educated', 0.4 to 'little educated', 0.6 to 'educated', 0.7 to 'medium educated', 0.8 to 'highly educated' and 0.9 to 'very highly educated'. Based on the membership values the learner profile information can be retrieved and classified more precisely compared to the existing learner profile concepts.

Fuzzy IF-THEN rules are applied to make decisions on the learner preference based on the learner interest and learning style.

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

person(?p), has_learnerinterest(?p, ?sub),equals(?sub, "networking" & "data_communications")-> learning_content(?p, "Computer_Networks")

person(?p), has_learnerinterest(?p, ?sub),equals(?sub, "ethical_hacking" & "network_security")-> learning_content(?p, "Hacking")

person(?p), has_learnerinterest(?p, ?sub),equals(?sub, "app_development" & "mobile_development")-> learning_content(?p, Mobile_Application_Development")

person(?p), has_learnerinterest(?p, ?sub),equals(?sub, "multimedia" & "media") -> learning_content(?p, "multimedia")

person(?p), has_learnerinterest(?p, ?sub),equals(?sub, "networking" & "network communication")-> learning_content(?p, "Data Communications")

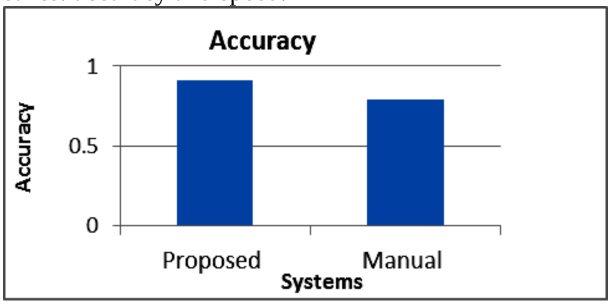
Overll Evaluation: The overall evaluation is done by separating the entire data sets into training and testing set randomly and then uses the same set to evaluate the accuracy each time. The accuracy is calculated using (6) or (7) for classification or prediction problems:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Number of Predictions}} \quad (6)$$

$$\text{Accuracy} = 1 - \frac{T_{predicted} - T_{original}}{\text{range (T)}} \quad (7)$$

where $T_{predicted}$ is the predicted target value, $T_{original}$ is the original target value in the dataset, and range(T) is the range of the target attribute T. The result shows that the accuracy obtained is reasonably close to each other.

Fig. 16 shows the graphical representation of results obtained during testing the rules on the learners' data sets of proposed system with the results of manual system based on two metrics: accuracy and speed.



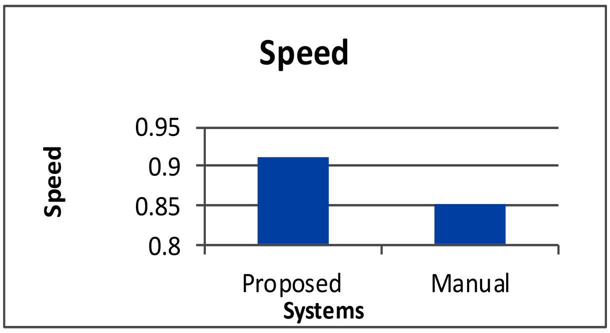


Fig. 16. Comparison of Proposed Vs Manual Systems

Hence, the proposed system has a reasonable accuracy of 91% with less time computational complexity thereby proving that the proposed system is able to make decisions on the preference of the new learners.

V. CONCLUSION

The proposed approach in this paper constructs a fuzzy ontology-based dynamic semantic learner profile. The construction of the learner profile is achieved with the use of ontology. The experimental results confirm that the proposed system is a good representation of learner's preferences with an overall accuracy of 91% and good speed. The approach is useful in predicting the learning preference of new learners from the learner profile. The experimentation is conducted with the help of software 'Java NetBeans IDE', 'Jena framework' and 'Protégé 4.2 beta' editor. The result would help the educators to analyze the performance of the learners' behavior using the learning system and also to frame the learning materials based on the learner's preferences.

The future research is to integrate the learner profile into the learning system for automatic detection of learner's preferences based on the learners' requirements which would help to design an effective adaptive system. Furthermore, future work is planned on improving and evaluating the usability of learner profile ontology in order to provide educators with better support.

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