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Ontology based E-learning framework: A personalized, adaptive and context aware model

Sohail Sarwar[1] · Zia Ul Qayyum[1] · Raúl García-Castro[2] · Muhammad Safyan[1] · Rana Faisal Munir[3]

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Abstract

Enhancing the degree of learner productivity, one of the major challenges in E-Learning systems, may be catered through effective personalization, adaptivity and context awareness while recommending the learning contents to the learners. In this paper, an E-Learning framework has been proposed that profiles the learners, categorizes the learners based on profiles, makes personalized content recommendations and performs assessment based content adaptation. A mathematical model has been proposed for learner categorization using machine learning techniques (a hybrid of case based reasoning and neural networks). The learning contents have been annotated through *CourseOntology* in which three academic courses (each for language of C++, C# and JAVA) have been modeled for the learners. A dynamic rule based recommender has been presented targeting a 'relative grading system' for maximizing the learner's productivity. Performance of proposed framework has been measured in terms of accurate learner categorization, personalized recommendation of the learning contents, completeness and correctness of ontological model and overall performance improvement of learners in academic sessions of 2015, 2016 and 2017. The comparative analysis of proposed framework exhibits visibly improved results compared to prevalent approaches. These improvements are signified to the comprehensive attribute selection in learner profiling, dynamic techniques for learner categorization and effective content recommendation while ensuring personalization and adaptivity.

Keywords Ontologies · E-Learning · Personalization · Adaptivity · Content Recommender

1 Introduction

The perceptible dominance of internet has affected every aspect of human life that can specifically be observed on academic landscape in the form of Electronic Learning (or "E-

✉ Sohail Sarwar
sohail.sarwar@seecs.edu.pk

Extended author information available on the last page of the article

Learning). The revolutionary advent of knowledge universality through E-Learning has entailed in upsurge of educational elite in societies through development of professionals by eliminating costs of workforce and infrastructure. Currently, these systems are playing a pivotal role in transforming information societies into knowledge societies through widespread delivery of didactic contents with a vision to educate future generation of learners (expected to grow from 100 million learners to 250 million by 2025 [3]). Such cyberspace driven learning is paving the way for building hubs of inventive activities through the emergence of E-Learning concepts [29] with target of maximizing the learner's productivity and effectiveness.

E-Learning is not confined merely to prompt deliverance of educational contents, rather it's a line of packages ranging from content development to maintaining profile of learners, aligning contents to respective learners as per their ability, from maintaining practice exercises to managing grading, adaptivity and personalization of learning material and searching from relevant educational repositories. The multifaceted and ubiquitous view of an E-Learning system has been illustrated in Fig. 1, aiming to improvise the role of E-Learning from information transmission to knowledge-construction [3] and deliverance targeted to enhance learner productivity.

With core functional components and services, the focus of our work remains on deliverance of learner specific contents (personalization), sequencing/re-sequencing of learning contents based on learner abilities, recommendation of contents to the learners and compliance of these learning artifacts to context-aware web 3.0. Each of these aspects is highlighted in the following.

Learner Attributes Profiling and Personalization of learning contents ensures that only relevant contents are presented to learner with respect to his cognitive abilities. It is contrary to a typical "one size fits all" approach that may not fully comprehend the learner's capacity to learn while presenting learning contents. Different attributes of learners have been considered while offering the learning contents instead of presenting the same contents to all the learners. These attributes are learner's academic performance, learning style, aptitude, background knowledge, and term-wise performance during the course etc. (methods for acquiring these attributes are discussed in section 3). Based on these attributes, learners are categorized into certain categories for recommending the suitable learning content (sequenced with respect to difficulty levels).

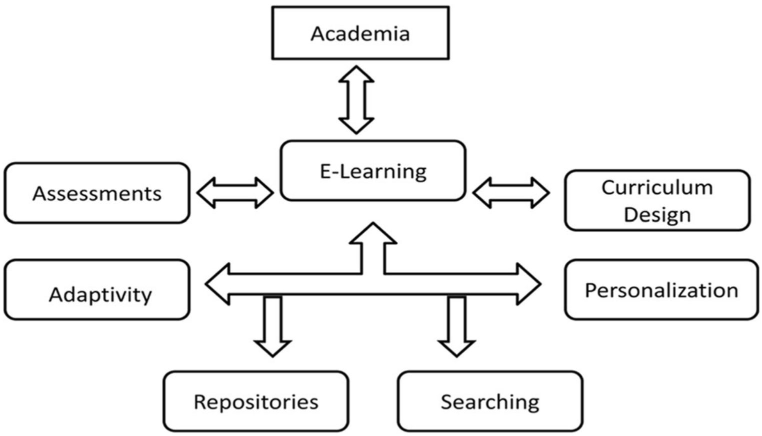

Fig. 1 Dimensions of E-Learning System

Learner Categorization: Once the picture of the learner's ability is clear by rightly categorizing the learner, learning contents may be offered keeping in view the learner's ability. This categorization has potential to offer twofold benefits i.e. what contents to be offered to the learner for first time and adaptivity of contents (performance-based sequencing/re-sequencing of contents during the course). Different techniques have been proposed for learner categorization [5, 17, 18, 29, 30, 40] that categorize the learners. However, these techniques have issues such as: considering academic attributes subjectively, ignoring learners' behavioral and demographic attributes, sort the learners into good and bad learners only, no reusing of information already categorized learners etc. The proposed technique exploiting the Artificial Neural Networks (ANN) for learner categorization uses learner profiles (combination of learner attributes) dynamically. Learners are categorized into one of the four categories of 'Novice', 'Easy', 'Proficient' or 'Expert' based on their profiles. Here it is worth mentioning that these learner categories were devised after a survey from the educational psychologists, learner evaluation from the behavioral and cognitive perspectives, literature [5, 17, 30, 40] and input from seasoned educationists and academicians. Once learners are categorized, a mechanism is desired to model the learning contents for every category of learners compliant with latest web technologies.

Learning Content: Web technologies have a paramount role in ongoing success of E-Learning applications for incorporating usability of learning contents, design of learning components and availability of digital repositories [7]. However, everything on current version of web is syntactical, machine-readable and not machine-understandable [37] making E-Learning solutions less flexible and less interoperable. Furthermore, context-aware alignment of contents to learners initially and after assessment is also an open research issue. These problems suggest porting of learning contents to context aware Semantic web (or Web 3.0) based on ontologies. Proposed framework exploits all the benefits associated with Web 3.0 through different ontologies i.e. course ontology models course of "Object Oriented Programming", assessment ontology to model quizzes and exercises. All the concepts (topic/sub-topic) in course ontology are annotated with a difficulty levels. These difficulty levels have been assigned to each topic or sub-topic with help of domain experts from industry as well as academia in compliance with prevalent standard such as SCORM/IMS [15]. Once learning content has been established in the form of ontologies and learner categories have been assigned to the learners, mechanism to recommend the learning contents needs to be devised for effective and efficient learning of the learners.

Knowledge based Learning Content Recommender: In order to make recommendations of learning content for learners, collaborative or content based educational recommenders use the ratings corresponding to learners, learning contents and content features [16, 24]. However, they may have issues of cold start/ramp-up (lack of historic information), early rater (no rating Information), and overspecialization (lack of knowledge about learner's level). Knowledge base recommenders are gaining much attention in E-Learning systems for not depending upon different ratings as collaborative or content based recommenders do. Another aspect of knowledge base recommenders is the use of ontologies that are naturally right representation of learning objects mimicking their relationships and interdependence (in same way as a "concept map"). Moreover, ontologies are equipped with features of reusability, interoperability and share-ability across different platforms while preserving the semantics of learning contents.

Keeping above in view, a rule based knowledge driven recommender is presented that semantically models the profiles of the learners and the learning contents in ontologies. Learning contents are recommended to the learners based upon their profile categories contained in ontology (No dependence on Ratings due to machine learning techniques based learner categories). Detail of this recommender is furnished in section 3.

Rest of the paper is organized as follows: section 2 provides a brief review of web 3.0 compliant E-Learning systems for effective learning, section 3 presents the proposed model of E-Learning framework in a modular view along with details of approach followed, section 4 provides evaluation strategies and performance of framework and section 5 concludes the work with a view of future directions.

2 Literature survey

A handful of literature is available on different aspects of E-Learning such as rationale for E-Learning system, modeling the learner profiles and learning contents for subsequent categorization, aligning learning contents and learner model with semantic web technologies and recommendation of learning contents to the learner etc. Each of these aspects is briefly reviewed in the following:

A philosophy, stating that learner's style should not be focused than learner's ability for personalization, has been discussed in [22]. Tests are used to estimate learner's ability dynamically. Different models such as domain model (classes/properties describing topics of domain and pedagogical relations), learner model (for learner's profile, preference and identification) and content models have been developed for building respective ontologies. Lastly, adaptive engine generates personalized contents based on learner's information coming from learner's model.

An unsupervised classification technique, linear regression, is used for modeling the quantity of accumulated knowledge [18] pertinent to a learner. It uses variables linked to the learning activity, user experience and accumulated knowledge. Categorization of learners is performed at concept level that in turn is evaluated based on percent concepts covered in knowledge. After assessments, learners are classified based upon two aspects i.e. quality of answers and the time consumed in answering. Contents of the discipline were divided into chapters where every chapter was modeled into concepts at a concept map. A classified model was created based on aggregates as a result of learner's experience in eventuation of learner's experience for recommending chapters/concepts in a discipline. 500 students, 5 disciplines, 5–10 chapters, 10–20 exams/tests were used to initiate learning and concept coverage to evaluate the predictive accuracy of approach in recommending learning contents.

An E-Learning system [25] based on cross similar ontologies has been proposed for users whose profile is maintained after getting his evaluation score from the perspective of domain specific and domain independent aspects. Here, the learner's profile (or learner model) for offering the learning contents is solely a function of assessing the score of the learner. Similarly, student's personality is maintained conceptually through coupling knowledge management techniques and ontologies in [12] (empirical research is still in progress).

The focus of work in [4] is to employ semantic technologies for persistence services in Learning Management Systems (LMS) through more expressive/flexible/heterogeneous/reusable representations. "Online communities" connected the external content base with learners/teachers to develop the "virtual communities". Also, internal and external contents have been linked to provide graph-based navigation in platform. A step ahead is SIOC (Semantically Interlinked Online Communities) that represents rich data from social web. Idea presented was applied on legacy applications by ending up in RDF graph that can be queried with SPARQL. Final framework was tested on big-data based technologies like Hadoop, Hbase, Flink etc. The entity centric nature of technique helps in identifying the resources via URI while competing the "linked data" environment for E-Learning resources in communities.

A system for betterment of knowledge management and for representing the associated data in learning management systems has been discussed in [21]. A domain ontology along with profile ontology has been presented through VARK model for learner's classification. A comprehensive view of m-learning is given along with semantic technology for location-independent learning. The aspect of personalization for learning content provision keeping in view capacity and skills of learner have been provided through VARK model of learning. ACM computation classification has been used to get baseline concepts for domain ontology. Profile of learner has been built by acquiring demographic information of the learner. Organization of the learning contents offered to the learner has not been elaborated though it is the core contribution of work as claimed. Also the aspect of personalization to recommend the relevant contents seems missing. Development of feedback system is envisioned as a future work. Also, it may aid in taking a step towards IoT (Internet of Things) based E-Learning system.

Lastly, few techniques [26, 39] claim to target the semantic web but formal and explicit descriptions of learners and learning contents using ontologies seem missing.

3 Proposed framework

On headway to developing the proposed semantics based E-Learning system, ultimate goal is to provide personalized and adaptive learning contents to the learners. This requires an insight into the cognitive abilities of the learners that can possibly be acquired once learner's attributes are profiled. So the proposed framework starts with accumulating the attributes of the learners as learner profiles followed by preprocessing of learner profiles to figure out most important ones having an impact on learner's performance. Based upon attributes unleashed by preprocessing phase, learners were categorized into different categories aligned with their learning abilities. These learner categories were used for recommending the learning contents (annotated with difficulty level) in a personalized way followed by adaptive recommendation of learning contents. An architectural view of proposed system is illustrated in Fig. 2.

3.1 Learner attributes profiler

A detailed view of learner attributes with an effective role in categorizing the learners, as exhibited during experimentation, needs to be discussed before getting into the details of categorizing the learner and respective content recommendation, Also, the way data was acquired to build the learner's profile and for recommending the learning contents has been presented as follows:

> *Learning Aptitude Test:* provides a basis for predicting an individual's ability, with training, to acquire some knowledge, skill, or set of responses. Also, it predicts an individual's potential with aptitude test scores. There are different domains covered in every test such as numerical aptitude, analytical skills, mechanical reasoning and verbal reasoning. Every test has certain score in ratio of total score but it does not depict the cognitive level of individual. Some meanings have to be attached to the score that can be in the form of Percentile or Stanine.

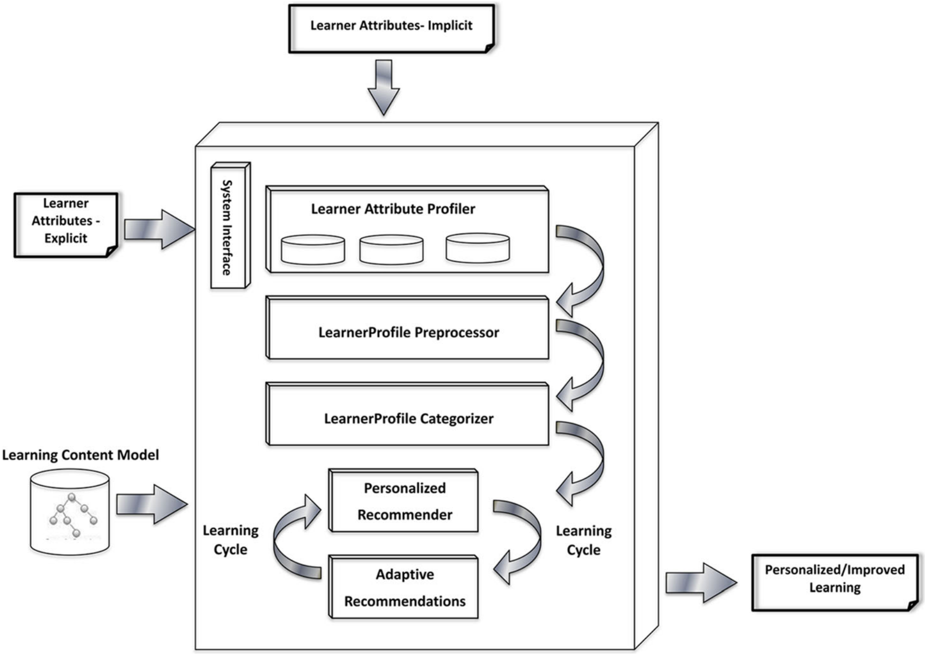

Fig. 2 Architecture of Proposed System

- Percentile is the percentage of candidates who fall below a particular raw score. e.g. a percentile of 65% means learner has better score than 65% of the class.
- Stanine [5] is the series of score represented on a scale from 0 to 9. Each of the score ranges classifies the given learner-score in to different categories. Stanine has been adopted as a scale to measure and categorize the learner based upon score achieved by each learner as shown in Table 1.

PreTests were developed for students with varying level of difficulty keeping in view their prior knowledge and pre-requisite score while consulting with domain experts. Pre-Test in our case comprised of programming questions developed using GAT Subject (CS) test banks [9], exercises from text books [13] and online quizzes [19]. Stanine standard used to categorize the learners based upon scores obtained.
Qualification of the learner is also a measure to decide upon cognitive skills of the learner i.e. to see if learner has attained undergrad, graduate or postgraduate courses while taking up the current course. Assumption: For current scenario, assumption is that learners have opted for undergraduate course (programming course).
Professional Experience is another factor in deciding upon how quickly, a learner can learn new concept/technology. There are three levels of experience considered in our case i.e. entry level, middle level and management level of experience.

Table 1 Stanine Scale for having Learner's Aptitude

	V. Low		Below Avg.		Average		Above Avg.		V. High
Stanine	1	2	3	4	5	6	7	8	9
Percentile	<= 4	5–11	12–22	23–40	41–58	59–77	78–89	90–95	>97

Learning Style is a phenomenon to assess the suitable teaching method for a learner that suits the learner. This decision is based upon description of attitude and behaviour, learning skill/style can be measured. Felder-Silverman model [36] has been used to measure the learning style of learner as shown in Fig. 3. It represents four dimensions of learner's personality having an impact on learning ability of leaner especially for hypermedia courseware. These dimensions are (1) Active/reflective (2) Sensing/intuitive (3) Visual/ verbal (4) Sequential/global. Learners are provided with a questionnaire to assess their learning behaviour for subsequent provision of learning contents.

CGPA is the academic measure of how a learner has been performing over the span of his degree. If student is taking course within the same degree, his CGPA in previous semesters is considered or that of his prior degrees is considered. (Assuming that learners are coming from computer science back ground).

Pre-Req GPA is another degree of performance that a person is exhibiting in pre-requisite course of the current course. (Assuming that "Fundamentals of Programming" is the prerequisite course of "Object Oriented Programming" course).

Age of learner is also an important factor for deciding upon learner-ability to grasp the ideas and concepts. It has been used to classify the learners as slower ones or quick learners.

Locale/Origin of learners has also been revealed as a factor with an impact on learner's academic performance and completion of degree [6, 27]. Each of the cities is labeled with a score reference to metropolitan, semi-urban and under-developed.

Learner Attributes acquired from different sources have been used to categorize the learner profiles with respect to their level of expertise and skills. These learner categorizations can be used for subsequent recommendation of learning contents to the learner. Learner profiles are maintained in "LearnerOntology" as ontology classes, properties and individuals through the Protégé tool (with requisite restrictions on concepts) as shown in Fig. 4. Moreover, few of the restrictions on ontology concepts through Description Logic (DL) constructs are illustrated in

Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
content_visit (-)	content_visit (-)	content_visit (-)	outline_visit (-)
Content stay(-)	Content stay(-)	ques_graphics (+)	outline_stay (-)
outline_stay (-)	example visit(+)	ques_text(-)	ques_detail(+)
Example_stay (-)	example_stay (+)	forum_visit (-)	ques_overiew
selfass_visit(+)	selfass_visit(+)	forum_stay (-)	ques_interpret (-)
selfass_stay(-)	selfass_stay(+)	Forum_post(-)	Ques_develop(-)
Selfass_twice_wrong(+)	Exercise_visit(+)		Navigation_skip(-)
Exercise_visit (+)	Quest_detail(+)		Navigation_overview_visit(-)
Exercise_stay(+)	Quest_facts(+)		Navigation_overview_stay(-)
Quiz_stay_results(-)	Ques_concepts(-)		
Forum_visit(-)	Ques_develop(-)		
Forum_post(+)	Quiz_revisions (+)		
	Quiz_stay_results (+)		

Fig. 3 Questionnaire to measure the learner's learning style [36]

Fig. 5. Such representation of learner's profile as an ontological knowledge-base can provide an optimal representation of information with consistency among concepts, reduced redundancy and capacity to infer and reason for intelligent information retrieval. The process of acquiring the learner profile attributes from implicit as well as explicit sources has been explained in section 3.1.

This repository of learners has been used by Neural Networks for categorization of learners. The performance of machine learning techniques greatly relies on the quality of the data set used for training, so it is important to provide a glimpse of such dataset. In total, there were profiles of 600 learners, each having 12 profile attributes for correctly categorizing the learners. Here it is worth mentioning that 600 profiles were available from three universities (200 learners from each university), each having four sections of course on Object Oriented Programming (every section having 50 learners). These learners were enrolled in sections Computer Science (Morning), Information Technology (Evening), Information Technology (Morning) and Information Technology (Evening). Details of universities have been furnished in section 4.3.

3.2 Learner categorizer - *LCHAIT*

In order to categorize the learner profiles, a novel technique has been proposed named *LCHAIT. LCHAIT (Learner Categorization with Hybrid of Artificial Intelligence Techniques)* is hybrid of two machine learning techniques named Case based Reasoning *(CBR)* [2] and Artificial Neural Networks *(ANN)* [31]. For new learners, profiles are retrieved in the same fashion as in the CBR retrieval phase using certain similarity metric [1]. Among the retrieved ones, cases that can be utilized are reused and the rest of them may be adapted for usage. The

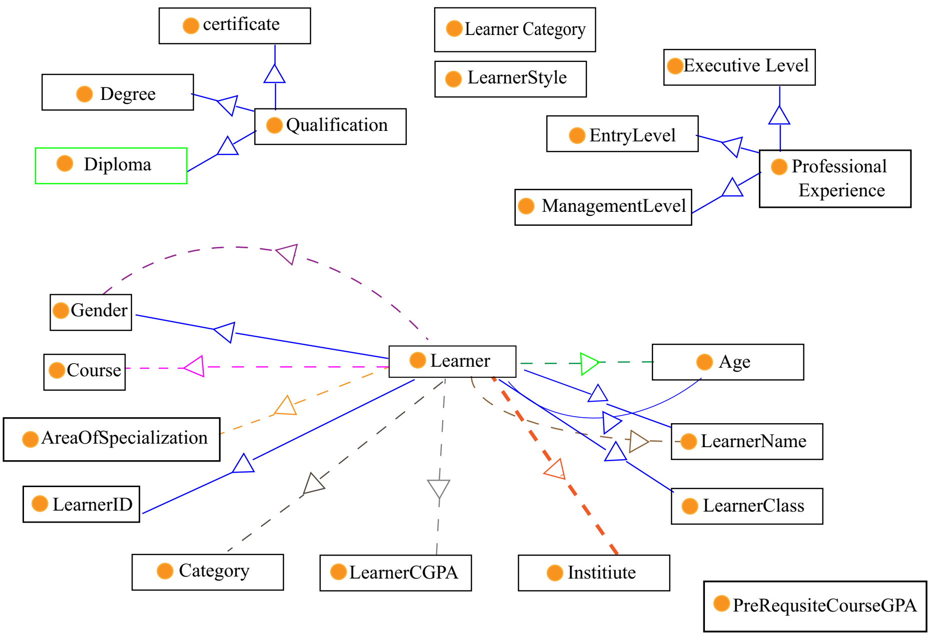

Fig. 4 A Snippet of LearnerOntology with learner concepts

Fig. 5 DL Restrictions on concepts of LearnerOntology

ANN model, used for categorization of learners through CBR's adaption phase [23], is trained over the retrieved cases instead of trained on learner profiles contained in whole case base. Once the learner category is assigned to the learners into any of the four categories by the ANN, the profile is retained into the CBR's memory for re-use.

Case based Reasoning (CBR) has been selected due to its inherent capacity of maintaining the prior knowledge into its repository and reusing the past knowledge maintained. In order to retrieve the most relevant cases the same similarity metrics were used i.e. Tvesky's Ratio Model with same similarity threshold as previously. The business logic for component of CBR has been implemented using JAVA.

Fuzzy Logic (FL) has been employed due to its inherent suitability for classifying (categorizing) the objects under consideration that are "learner profiles" in this case. It categorizes the learners based upon their profile attributes (in the form of qualitative attributes) that are mapped to input ranges. Crisp input comprises of profile attributes of learner which is fuzzified, evaluated using a set of rules in the rule inference engine in order to produce learner's category; which is defuzzified for providing the requisite output. Learner attribute variables (feature attributes selected) corresponding to learner's profile are fed to the FL model in crisp form scaled over a numeric range. For example *PreTestScore* is an input variable with four ranges for Fuzzification through membership function i.e. poor (0–1.9), fair (2–4.9), good (5–7.9) and very good (8–10) based on concept given in [116]. These variables are fuzzified using the "Gaussian" membership function. The Rule base of the fuzzy inference engine (*if-then-else*) aids in deciding the category of the learner. Centre of Gravity method has been used to defuzzify the output of rule inference engine.

The variant of Neural Networks named MLP (Multi layer Perceptron) has been selected due to its ability of regulating network weight in order to minimize the *Mean Square Error (MSE)*. The MLP model was implemented using Neural Pattern Recognition tool of Matlab 2015a with standard weights and activation functions. Besides, another script was written in Matlab separately for experimenting with different number of neurons and middle layers. The input layer contained 7 neurons, 2 hidden layers each with 8 neurons and an output layer with 1 neuron.

The ANN model has been trained over the data repository containing learner profiles as discussed in section 3.1. In order to train the ANN model, the dataset fed (i.e. the whole set of 600 profiles) was divided into three bins of training set, validation set and testing set. Training and validation phases were targeted for making adjustments to the ANN model in reference with its error rate and generalization. Subsequently, testing phase measured the model performance with respect to its accuracy. Moreover, it aids in deciding if the ANN model needs to be retained provided that the error rate exceeds that expected. The dataset of proposed model was divided into three sets with a division of 70% for training, 20% for validation and 10% for testing of the ANN model. The performance of the model during validation/testing phases has been measured in terms of how accurately learners have been classified while considering the associated costs

```
% Setup Division of Data for Training, Validation, Testing
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 20/100;
net.divideParam.testRatio = 10/100;
```

A mathematical representation of proposed approach has been given in the following to formally describe the process of learner categorization:

Let (LA) represent an attribute of learner profile (LP) in the form of a matrix with dimension of m x n:

$(LP)_1 = (LA)_1, (LA)_2, (LA)_3, \text{--------} (LA)_n$
$(LP)_2 = (LA)_1, (LA)_2, (LA)_3, \text{--------} (LA)_n$
$(LP)_3 = (LA)_1, (LA)_2, (LA)_3, \text{--------} (LA)_n$
- - - - --------------
- - - - --------------
$(LP)_m = (LA)_1, (LA)_2, (LA)_3, \text{--------} (LA)_n$

where $((LP)_m \times (LA)_n) \in ф^{m \times n}$; here ф represents the case base of CBR, m=1400, n=9.
Also,
if $P € ф^{m \times n}$ and $Q = \{(LA)_1, (LA)_2, (LA)_3, \text{--------} (LA)_n\}$
$y = S(P,Q) = \{1 \text{ if } R \geq t\} \vee \{0 \text{ otherwise}\} \wedge S(P,Q) = \{1 \text{ if } R \geq 0\} \vee \{0 \text{ otherwise}\}$
Where
P: represents cases in the case base,
Q: represents a query case,
T: threshold of similarity for reusing/revising a case,
R: is similarity rank calculated using Tvesky's ratio model as given below:

$$R_i(P_i,Q_i) = C(P_i, Q_i) / C(P_i, Q_i) + D(P_i, Q_i)$$

Where
C (P,Q) is the number of common elements among P and Q.
D (P,Q) is the number of differing elements among P and Q.

In our case, since the output is the discrete random variable with discrete time distribution; and if current output (i.e. selected profile); we can predict learner category 'y + 1' which is function of current output 'y(n)' and profile values 'ф(n)' in the case base:

$$y\,(n+1) = f\,(ф(n), y(n))$$

For ANN model,

inputs are $(y_1,y_2,y_3\text{-------}y_n) € \{(LP)_1, (LP)_2, \text{------}, (LP)_m\}$ where $(y_1,y_2,y_3\text{-------}y_n) \leftrightarrow (LP)$
weights (w1, w2, - - - - wn) € W with one output
$y(n+1) = \sum i=1$ to n satisfying F: y^k such that $F(y_i,w_i) = f(yi, wi) \in ф$
y(n+1) is the learner category predicted.

A linear model of input, state and output can be represented by:

$$\begin{aligned} d_x/d_t &= A_x + B_y \\ y &= C_x + D_y \end{aligned} \tag{1}$$

where y ϵ $\phi^{maximum}$ with input x ϵ $\phi^{maximum}$ (x^n) is state and y ϵ $\phi^{maximum}$, (x^p) is the output.

Consequently,

$$A \in \phi^{n \times n} \qquad B \in \phi^{n \times m} \qquad C \in \phi^{P \times n} \qquad D \in \phi^{P \times m}$$

D is called feed through term. The polynomial form of eq. (1) can be given as:

$$\Phi(d/dt).Y = M(d/dt) \times \text{with}\, y = \text{cal}(x, y)$$

The proposed technique *LCHAIT*, exploiting the notion of hybrid machine learning techniques for learner categorization, would target the E-learning systems by modeling learner profiles through ontology. It needs to be dynamic enough for building a learner's profile automatically with implicit parameters from real time data sources and explicit parameters acquired from the learner. The profile of a learner would be modeled by considering demographic, academic, behavioral, and inclinatory aspects of the learner in an ontology named LearnerOntology to benefit from semantic web technologies. After building profile of learners, proposed technique (*LCHAIT*) would classify the learners by exploiting the retrieval phase of Case Based Reasoning (*CBR*) and employ Artificial Neural Networks (*ANN*) in adaptation. Moreover, data repository of the E-learning system may be updated with latest information of learner category. This aids in dynamically reusing the profile of existing learners in classifying upcoming learners.

3.3 Learning content model

In any learning management system, learner and learning content are the key factors contributing towards success of any system. Apart from maintaining the learner profile (as discussed in section 3.2), learning content modeling needs to be maintained as well. Learning content model is the representation of the properties of a course and more specifically one in object oriented programming languages along with contents.

Learning contents represented by topics and subtopics each corresponding to a concept in ontology as shown in Fig. 8 through 'CourseOntology' where every concept refers to a topic. The topics having a strong relation have been represented as sub-concepts of a concept in a hierarchical fashion. For example, concepts of OOP_Abstraction, OOP_Inheritence, and OOP_Polymorphism are sub-concepts of OOP concept. Moreover, the concepts presented in the course are stamped with difficulty level, programming language (since three languages are modeled in ontology) and number of weeks. These aspects aid in offering contents to a learner aligned to learner's cognitive level.

Mapping among respective concepts from learner ontology and learning contents ontology is provided through a rule based system. On one hand, rule based recommender ensures aspect of personalization and on other side performance (or evaluation) based adaptivity is incorporated. Based upon performance of learner in certain topics and weeks, learning contents are re-sequenced or category of learner is updated. After half of the semester, learner's performance is evaluated subject category in order to reassign the learner category. The key parameters of adaptivity are the target-model scores for each of the category, course week, assessment score (weighted scores obtained in quizzes, assignments, exercises and class tasks) and number of times learner's content level has been upgraded and downgraded while offering the contents.

Each of the topics is connected to sub-topics, pre-requisite topics and topics following the current ones (i.e. Post topics). Every topic is connected to a Learning Object (LO) that refers to repository containing learning contents in the form of text files, images or videos. Every learning object is annotated in such a way that it can identify and represent a topic in entirety as modeled in Figs. 6 and 7 respectively (Table 2).

LO111 means, it is a LO number 1, offered in week 1 with difficulty level of 1.

Here it is worth mentioning that ontology illustrated in Fig. 8 is specific to the course of OOP. In order to consider any other course, the contents need to be annotated generally as shown in Figs. 6 and 7. However, a specific representation of contents will be required to a detailed level of granularity as shown in Fig. 8.

3.4 Knowledge based recommender

Once contents of a topic are modeled in ontology and connected to respective LOs, there is need to recommend each of the learners with learning content by Knowledge based Adaptive Semantic E-Learning Recommender (KASER). For example, a novice level learner is recommended with learning contents of novice type or an expert level learner may be offered expert level contents (i.e. incorporating the feature of personalization). Once learning activity is performed, learner is undergone the phase of assessment on bi-weekly basis. These assessments comprise of an average score learner has attained in assignments, quizzes and exercises. Moreover, learner's performance is tracked over the weeks. If learner keeps on performing as desired (i.e. meets the target model criteria) for two weeks, contents that are offered to him are upgraded with a next level category of contents i.e. learner previously offered with novice level contents is presented with easy level contents and so forth. Likewise, if performance of a learner is not up to the mark (i.e. does not meet the target model criteria), he is down-graded to easier level of contents i.e. a learner offered with expert level contents is presented with proficient level contents and so forth. Furthermore, if learner's performance does not perform up to the target model, category of the learner is downgraded or upgraded for presenting the respective learning

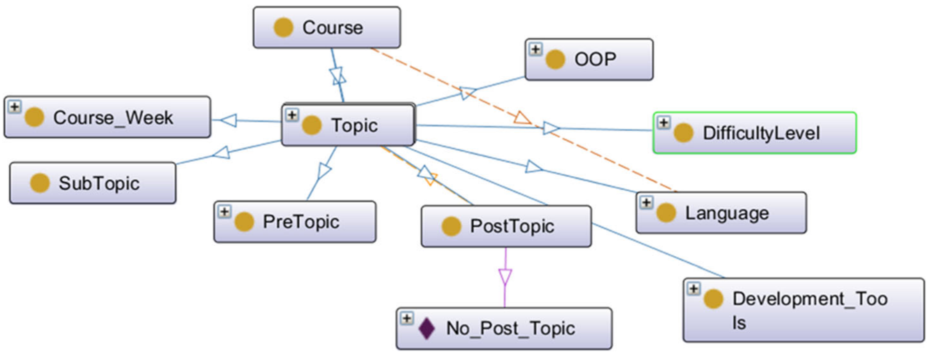

Fig. 6 Domain representation of CourseOntology

content. This maneuvering of contents by sequencing/re-sequencing contents is driven by the “relative grading” that shuffles learners (in different categories) to ensure aspect of adaptivity.

	Below Avg	Average	Above Avg	High
% Clusters	Novice	Easy	Proficient	Expert

Pseudo code for rule based semantic content recommendation (KASER) is given in the following:

```
Public Topic recommendLearningTopic (learnerID, learnerCat, cWeek) {
cAssessScore = getcurrentAssessmentScore(learnerID);
tModelScore = getTargetModel(learnerID,cWeek);

If (cWeek==1 or cWeek==2 && learnerCat==‘expert’) then
        contentType = proficient;
If (cWeek>2 && cWeek<5) {
        if (learnerCat==‘novice’ && currentAssessScore >= tModelScore)      then
                contentTopic= postTopic;

        else if (learnerCat==‘novice’ && currentAssessScore < tModelScore) then
                        contentTopic= preTopic;
                        contentType = novice;
        else if (learnerCat==‘easy’ && currentAssessScore < tModelScore) then
                        contentTopic= preTopic;
                        contentType = novice;
                        contentType = easy;
  }
 assignlearningContent based On:
        [week and learnerCat and assessmentScore and targetModelScore]
        Topic=pre-topic or Topic =post-topic
 }


 Public int getcurrentAssessmentScore(learnerID)
 {
 assessmentScore = [(assignmentScore + quizScore + exerciseScore)/ 3]
 return %assessmentScore;
 }
 Public int getTargetModel(learnerID, cWeek){
 category = getCategoryofLearner(learnerID);
 Relative grading to decide the target.
 Tgt=(Score - Mean)/SD
 If (category) then
        targetScore
 return %targetScore
 }
```

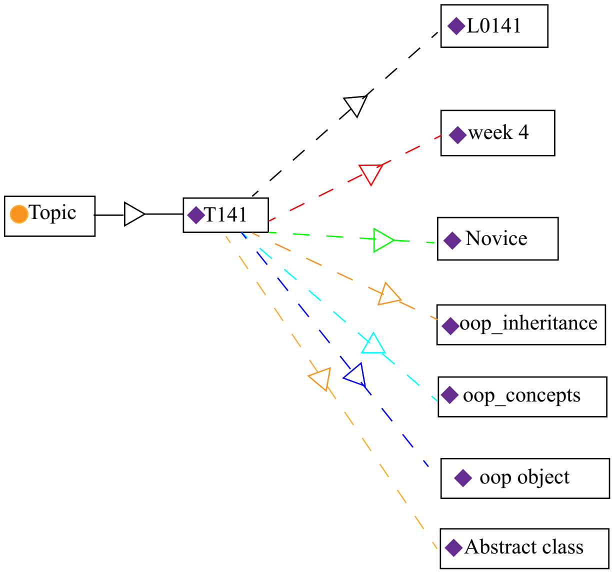

Fig. 7 Topic with respective Instances and LO representation

4 Results and evaluation

The evaluation of proposed system is performed from two perspectives i.e. Evaluation of Ontological models through standard ontology evaluation techniques and experimental evaluation of proposed techniques. The experimental evaluation of system has three aspects (a) Accuracy of learner categorization (b) Precision of KASER in content recommendation and (c) Impact of Proposed system on learner's performance over a temporal scale.

4.1 Ontology evaluation

There are two aspects of evaluating the health of ontologies; First, the ontologies which have been used in the learner categorization as well as in the content model and second is to compare proposed ontology model with contemporary ones [11, 35].

Table 2 Representation of Typical Topics and LO as Ontology Instances

Topic	Topic Name	SubTopic	Language	Week	Learning Object
T111	OOP	Objects	1	1	LO111
		Inheritance	1	1	LO112
		Abstraction	1	1	LO113
		Encapsulation	1	1	LO114
T281	Pointers	Declaring Pointers	2	8	LO291
		Ref/DeRef Pointers	2	8	LO292
		Array Pointers	2	8	LO293
		Function Pointers	2	8	LO294
T3A1	Threads	Threading	3	10	LO3A1
		Events	3	10	LO3A2
		Sync. Threads	3	10	LO3A3
		Semaphores	3	10	LO3A4

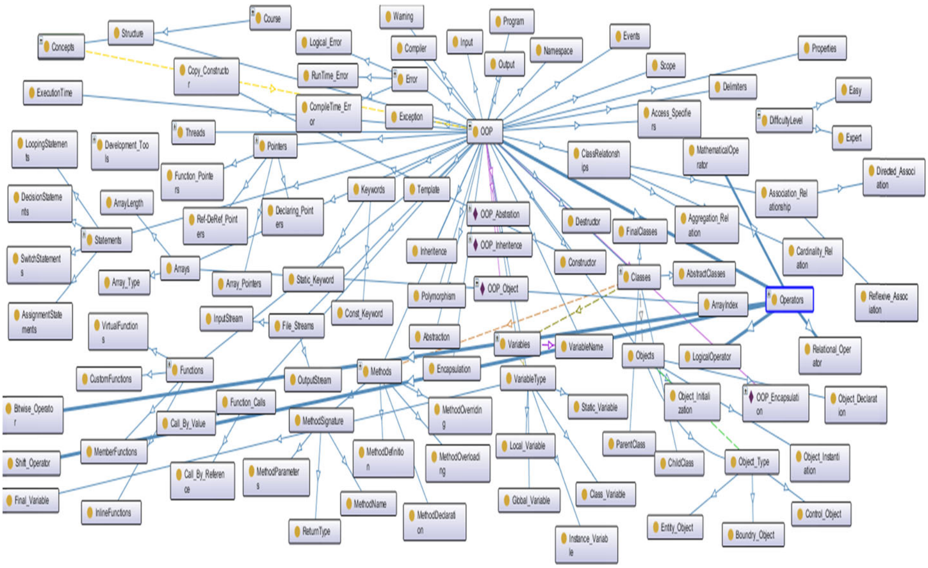

Fig. 8 CourseOntology for OOP Course

4.1.1 Consistency of ontological models

Ontology consistency is evaluated using Pellet [38] reasoner and built in ontology tester of Protégé (mainly checks the disjoint, inverse and domain/range). This reasoner ensured that ontology is consistent and can be utilized for semantic E-learning operations without creating any inconsistency among concepts/classes and their hierarchical relations (Fig. 9).

4.1.2 Completeness (domain coverage) of ontological model

The completeness metric of the ontological model determines the comprehensiveness of the domain coverage for E-Learning systems. Proposed ontology models cover almost all the concepts related to characterization of learner, domain of a typical university course,

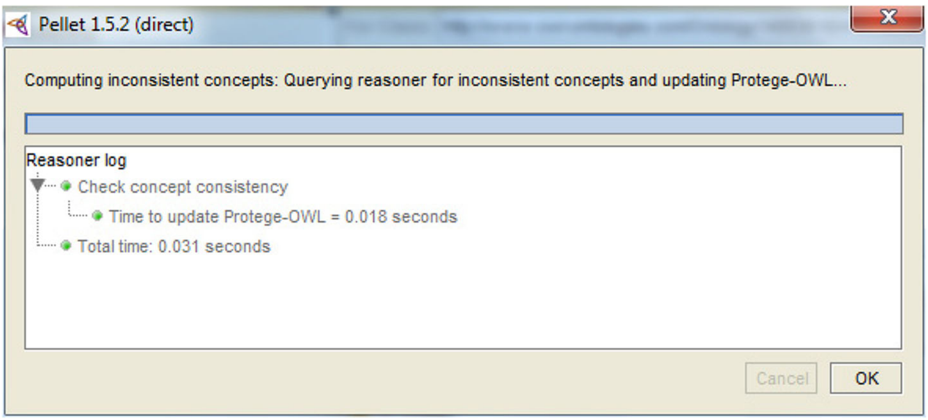

Fig. 9 Consistency Check of Ontology Model

assessment modules and course of OOP. Moreover, ontology models comprise of necessary axioms ensuring redundancy-free terms and irrelevant axioms.

In order to verify the ontology coverage for fully modeling the domain of E-learning, SCORM [14] was used as a point of reference besides the competence of domain expert. SCORM enlists all aspects i.e. course content development, exams (assessment), quizzes, exercises, exams etc.

4.1.3 Expandability and reusability of ontological model

The ontology model specified for the course i.e. CourseOntology, is expandable. This ontology can be expanded with new concepts to further elaborate the contents of course. Similarly, LearnerOntology may be updated with any new field to be added to build the profile of learner. Moreover, semantics-aware contents can be offered to the learners at all stages of learning cycle.

4.1.4 Quality of ontological model

Quality of Ontology evaluation refers to fault diagnosis and fixation of revealed gaps (or pitfalls). It is cohesive part of tasks involving ontologies for technically validating the ontology quality. In order to evaluate the overall quality of ontologies (in terms of faults), two of the most prevalent techniques have been selected i.e. OOPS (Ontology Pitfall Scanner) [20] and Ontoclean [10].

A technique named OOPS (Ontology Pitfall Scanner) has been employed that diagnoses and categorizes the faults reference to their criticality fully aligned with quality standards. These categories are normal, minor, important and critical. OOPS findings for LearnerOntology are given in Table 3 with no critical pitfall.

OntoClean meta-properties have been applied on classes and properties to check for subsumption relations and ontology model with violations. The patterns with violations in model were detected and removed using *SPARQL* queries. OntoClean offers logic based argument in validating the ontological and taxonomical relationships through meta-properties of Rigid, Identity and Unity. These meta-properties were applied to all the ontologies. However, a brief description of meta-properties over the concepts of "LearnerOntology" and "CourseOntology" has been furnished in the following:

Table 3 OOPS based evaluation of *LearnerOntology*

Pitfalls Category	Ontology Pitfall	Importance Level			
		Normal	Minor	Important	Critical
Structural Dimension	Modeling Decisions- P [36]			√-1	
	Wrong Inference	√			
	No Inference P [15, 24]		√-4	√-3	
	Ontology language- P [11, 28, 34]	√			
Functional Dimension	Real World Modeling – P [17, 37]		√-3	√-1	
	Requirements Completeness				
	Application context- P [8, 33, 35]	√			
Profiling Dimension	Ontology Clarity – P [13, 32]		√-2		
	Ontology Understanding- P [15, 24, 32]		√-3	√-2	
	Ontology Metadata – P [6, 11]	√			
Consistency	P [18]			√-1	
Completeness	P [15, 17, 24, 37]		√-2	√-3	
Conciseness	P [5, 29]	√			

- **LearnerOntology**

– *Learner* concept complies with meta-properties of Rigid, Unity, and Identity.
– *Course* concept is *subclassof Academic* with meta-properties of Unity and Identity.
– *Topic* concept has the meta-property of Rigid and Unity

- **CourseOntology**

– *OOP* concept is *subclassof program* with meta-properties of Unity, and Identity.
– *Statements* concept is *superclassof Keywords* with meta-properties of Identity and Rigid
– *Inhetitence* concept is with meta-properties of Identity, Unity and Rigid

4.2 Comparative analysis of ontologies (domain coverage)

As discussed in section 3.4, a comparison of proposed ontology models (in *KASER*) has been made with ontological contents [14, 38] for comparison of ontology with respect to the coverage of domain (with prevalent techniques named SRS and PAeLS respectively).

In prevalent techniques specifically [14, 38], ontologies are focused towards personalization of presentational aspects than actual contents to be presented to the learner. Secondly, domain ontology is not very comprehensive to cover all aspects of a course in semester of a class. Lastly, the contents presented in ontologies are very specific and trivial with very few relations among concepts in terms of object properties and data properties. Our ontology, on the other hand, is comprehensive enough to cover all the requisite concepts for any programming language course in certain semester. Also, the aspects in content model contained in the form of ontology fully describe the object oriented programming languages at finer level of granularity (C++, C# and Java are modeled in ontology). Here a comparison is presented with respect to the coverage of domain i.e. number of concepts, number of object properties and the data properties as shown in Fig. 10. The comparison in terms of coverage of concepts asserts the superiority of proposed technique for having better concepts coverage, properties and profiling of the learners.

4.3 Evaluation of learner categorizer (*LCHAIT*)

In order to measure the performance of *LCHAIT* and its comparison with existing knowledge base techniques i.e. Fuzzy Logic (FL) [28, 34], Case based Reasoning (CBR) [28] and machine learning technique Neural Networks (NN) [8], a data set comprising of the profiles of 1000 students was used. In order to build the profiles, data of students was acquired from different universities (GCU Lahore,[1] UAAR Rawalpindi,[2] and Iqra University[3]), with different institutes (Computer Sciences and Management Sciences, Engineering Dept), and different courses (Fundamentals of Programming, Organizational Behavior, Data structures, Marketing and Business Law). This data diversity is purposefully introduced to comprehensively cover variety of cases in

[1] http://www.gcu.edu.pk/
[2] http://www.uaar.edu.pk/
[3] http://iqra.edu.pk/isl/

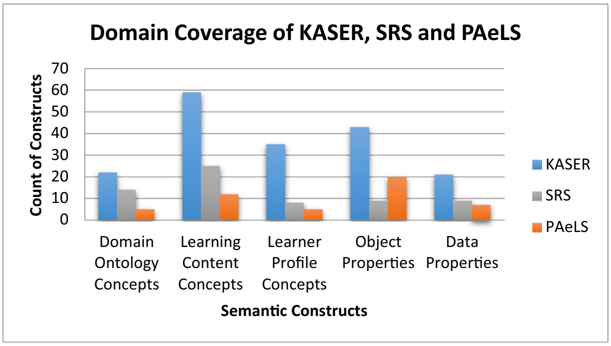

Fig. 10 Comparative Analysis of Domain Coverage of Ontologies

our data model. Comprehensiveness of data models ensures an effective training approach of machine learning models independent of any biases (i.e. lack of coverage of cases or overfitting).

There were eight sets of new learners' Profiles (each set having profiles of 50 learners) given randomly to retrieve similar profiles through CBR's similarity metric as explained in section 3.4.

Out of 1000 learner profiles, 700 were used as training set of ANN model and 300 were used as validation set of ANN model in a random fashion (n-fold cross validation). Whereas, eight sets of new learner's profiles were used for testing of ANN model. Effectiveness of ANN model was measured through its accuracy in assigning category to the learners presented as validation set.

LCHAIT has been evaluated through variation of training set and validation set with same testing sets as described in above scenarios. Learner profiles retrieved through CBR's retrieval phase are used for training of ANN model. Profile retrieval is carried out without provision of category, whereas retrieved cases contain the learners' category. All eight sets (each having 50 profiles), serving as validation set, retrieve profiles (with 60% similarity) which are used to train the ANN model for accurately predicting category of learner.

A consolidated view of predictive accuracy exhibited by all four methods is shown in Fig. 11, where every value is percent depiction for performance models. In other words, it is the picture of classification accuracy to rightly predict learner's category without taking into account aspects of precision and recall.

Fuzzy Logic has shown an average accuracy of 29.67% in retrieving right cases. CBR has accuracy of 47.35% followed by accuracy of ANN i.e. 57.52%. *LCHAIT* has shown better accuracy than other techniques i.e. 70.84%. The reasons for superior performance of *LCHAIT* over Fuzzy Logic, Case based Reasoning and Neural Networks are discussed below.

Fuzzy logic, driven through knowledge in *Rule Inference Engine*, seems not adaptive to comprehend different scenarios with different parameter values due to static rule base. For example, profile attribute of *PreTest* has higher impact in classifying the learner to certain class but rules in the rule base cannot comprehend these relationships. Such variation in profile attributes are not handled adaptively by Rule-base of fuzzy logic.

The performance of Case based Reasoning is greatly dependent upon selection of right contents during retrieval phase through similarity metrics. Here, relevant profiles are selected based on static rank that inherently would ignore cases even if they are to be selected with a least margin without taking into account any exceptions.

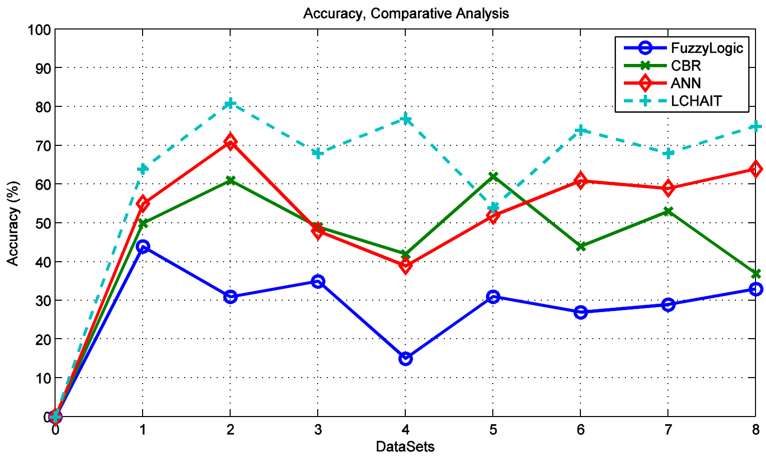

Fig. 11 Comparative Analysis of Learner Categorization: Accuracy

Neural Networks exhibits better performance than FL and CBR due to its dynamic and adaptive nature. Besides input and output layers, there were two middle layers, each containing 15 neurons in order to get trained, validate and test the learner profiles for right categorization of new learners.

On the other hand, the hybrid approach named *LCHAIT* shows better performance than rest of the contemporary techniques in terms of performance parameters so far. *LCHAIT*, contrary to ANN, uses only one hidden layer with 8 neurons on middle layer (computationally less expensive). Effectiveness of *LCHAIT* is signified by phase of preprocessing (both for attributes and data), by data used for training and more importantly by training of NN model on most relevant profiles retrieved through CBR's profile retrieval phase.

4.4 Evaluation of personalized content recommender (*KASER*)

One of the major focuses of proposed research is to provide the learning contents to the learner aligned with learner's capability i.e. personalized contents. After learner categories are finalized and learner contents have been modeled, a mechanism for respective content recommendation needs to be devised. A rule based knowledge driven recommender named (KASER) is presented in this research work that recommends semantically modeled learning contents in ontologies to respective profiles of the learners.

A class of 40 learners was selected for evaluation purpose with profiles available in learner ontology. These profiles (annotated in ontology with different attributes) were used for recommending the suitable contents. In order to compare and analyze the accuracy of recommendations made by the proposed system named *KASER (*Knowledge based Adaptive Semantic E-Learning Recommender*)* keeping in view the profiles of the learners.

Contents recommended by learner were also recommended by domain experts in order to assert the degree of correctness shown by proposed system. During initial weeks, recommendation of contents while ensuring the personalization was done by rule-based recommender. Here degree of correctness for contents offered was main focus before assessing the learner. In order to assert the level of agreement between contents recommended by *KASER* and the ones recommended by Domain Expert (DE), Kappa coefficient has been used as shown in Table 4.

Table 4 KASER's Personalized Content Recommendation Validated by Domain Experts (DE)

No of Weeks	Recommendations by KASER		Accuracy Validation by DE		Kappa 's Coefficient
	Topics	Sub-Topics	DE 1	DE 2	
1–2	3	5	72%	81%	74%
3–4	4	9	83%	77%	79%
5–6	4	7	80%	85%	81%
7–8	3	5	83%	68%	72%
9–10	2	6	76%	84%	78%

An average of contents recommended by domain experts was taken. This average was used alongside the contents recommended by *KASER* for calculating the Kappa's coefficient. The range of Kappa's co-efficient is shown from 70 to 85. As per research standards anything above 65% is adequate level of agreement [35].

Figure 12 provides a detailed insight to the weekly progress that learners made while following the learner activity through conventional system, with PAeLs [11] and semantic recommender (KASER). The assessments were designed such that depth of knowledge, coverage of contents and impact of remedial exercises could be evaluated.

The average of scores that learners acquired in weekly assessments, exercises and quizzes is taken for all 8 weeks of summer semester in 2016 for course of "Object Oriented Programming".

It may be observed that learner's performance is substantially improved when learning process is carried out by following the proposed approach (*KASER*). The results exhibited by *PAeLS* [11] appeared to be better than conventional approach; however, a visible performance difference can be seen compared to *KASER.* Few of the distinctive reasons for better performance of proposed approach are comprehensive number of parameters used for learner's profiling, effective learner categorization through dynamic machine

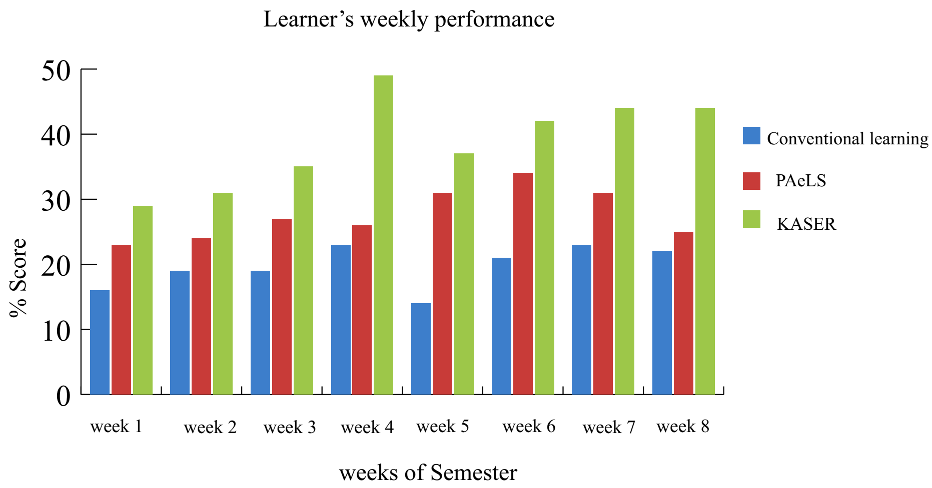

Fig. 12 Learner's Performance: Weekly Impact of Conventional Learning, PAeLS and KASER

learning techniques, modeling of learning content at various levels of difficulty, personalized and effective content recommendation of contents based on learner ability and assessment based adaptivity of learning contents.

Here, it is worth mentioning that learners undergoing the process of having their profiling, their categorization, content recommendation, assessments and content adaptation were aware of the learning cycle and process. All the learners from participating institutions were taken into confidence and accepted the research outcomes for improving overall learning approach.

4.5 Impact of *LCHAIT* and *KASER* on learner's productivity

The evaluation process of proposed approach did not span over a week or a term rather learners from three batches in three years were categorized, underwent learning-assessment cycles and their performance was recorded. An aggregate of performance metrics for implementing the envisaged idea with personalization and adaptivity of learners was recorded. Figure 12 provides a detailed insight to the year-wise performance of learners in mid-term and final-term exams. The average of these scores was taken in for semester in 2015 for course of "Object Oriented Programming". Here, assessment results of learners were recorded without taking into account any of the processes in proposed approach (i.e. conventional approach as shown in Fig. 12).

In year 2016, with new group of students, learner categorization based content recommendation was made and subsequently results were recorded. The content recommendation was done with feature of personalization i.e. learning contents with respective level of difficulty for the relevant learners. Lastly, the results with features of assessment based content adaptivity were recorded in year 2017 on same patterns as in previous two years.

A consolidated view of the learner's performances in mid-terms and final-terms of year 2015, 16 and 17 is illustrated in Fig. 13.

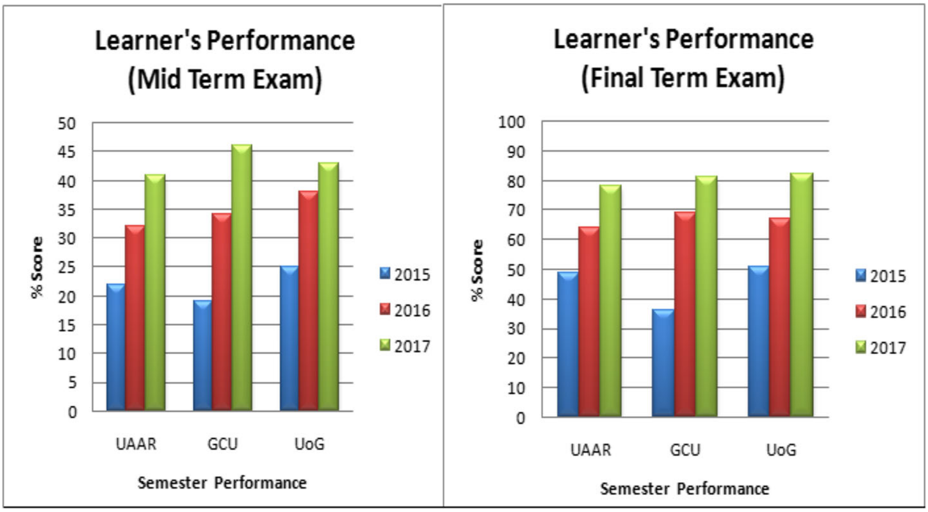

Fig. 13 Learner's Performance in Mid/Final Terms in Year 2015, 16, 17

A thorough evaluation of proposed E-learning framework has been provided in preceding sections from two perspectives i.e. evaluation of ontological models and experimental evaluation of different dimensions of proposed framework. Ontologies have been evaluated based upon standard techniques such as OntoClean, OOPS, consistency and domain coverage as given in section 4.1. Ontologies used in modeling have been found complete, consistent and rich in terms of knowledge when compared to prevalent models (as given in section 4.2). The preliminary implementation of proposed framework shows an improvement in performance of learners as stated in section 4.2 to 4.4. The evaluation of techniques employed for learner profiling and categorization is explained in section 4.2 and 4.3. The results assert *LCHAIT* as a better technique than contemporary ones due to hybrid of neural networks and case based reasoning. The performance of knowledge based content recommender is evaluated in section 4.4 where accuracy of recommending the learning contents to learners is presented. Finally, an overall impact of learner's performance is presented over different temporal scales i.e. learner's weekly performance, performance in mid-term exams, improvements in final-terms exams and overall impact of proposed approaches on learning capacity of learners.

5 Conclusion and future directions

Keeping in view the technological advancements, potential increase in number of learners and their learning requirements; ontology based personalized and adaptive E-learning framework has been proposed. The rationale for proposed system has been provided in detail while justifying its alignment with prevalent technological trends (especially those of web3.0 technologies). One of the most important goals of E-learning systems is its effectiveness for improvising learner's productivity. So learner's productivity has been ensured through features of personalization and adaptivity while suggesting the learning contents to the learner.

A comprehensive set of learner attributes was shortlisted in order to build the learner profiles. The selected profile attributes were further refined for having the ones with maximum impact on defining learner's capabilities. Based on these profile attributes, each of the learners was assigned a category while keeping in view the cognitive skills of learners. A technique named *LCHAIT* was proposed that exhibited an effective degree of accuracy while categorizing the learners compared with rest of the techniques. The learning content annotated through ontologies and sequenced for learners of different category was recommended through a dynamic content recommender (*KASER*) with respect to learner's category.

Overall, performance of learners was recorded in order to measure the impact of proposed approaches on semester- basis (weekly performance, mid-term and final-term exams) in years 2015, 2016 and 2017 respectively. The performance of learners appeared to improve with gradual incorporation of proposed approach compared with conventional approach and PAeLs. Such improvement is courtesy to comprehensive learner profiling, dynamic learner categorization, personalized content recommendation, adaptive learning cycle and reusable learning contents modeled in ontologies.

We look forward to use the fuzzy logic for clustering the learning contents and subsequently the learners based on their performance. Besides, experiments may be carried out for learner categorization using another variant of neural networks i.e. Radial Basis Function (RBF) [33] that works well with limited training/validation sets. Moreover, Genetic Algorithms (GA) would be used for learner categorization. Another dimension may be to experiment with fuzzy logic by making its rule base dynamic through GA as done by [34].

Moreover, we will develop a generic ontology backed system capable of developing contents dynamically from any domain.

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Sohail Sarwar received the PhD degrees in Information Technology from National University of Science and Technology. Islamabad, Pakistan. He is currently a faculty member in the Department of Computing, University of Gujrat Pakistan. His research interests include e-learning, semantic technologies and knowledge engineering techniques. Lately, he has been part of Ontology Engineering Group, Universidad Politécnica de Madrid, Spain for research visit.

Zia Ul Qayyum is currently a Professor at University of Gujrat Pakistan. He received his Ph.D. degree in Computer Science from Leeds University UK in 2005. His research interests include Artificial Intelligence, Knowledge Engineering, Data mining, Semantic web and e-learning.

Raúl García-Castro is Assistant Professor at Universidad Politécnica de Madrid, Spain. He got his PhD degree in Computer Science and Artificial Intelligence from Universidad Politécnica de Madrid, Spain in 2008. His research interests include semantic technologies, ontology engineering, and ontology-based data integration.

Muhammad Safyan is Assistant Professor in Government College University (GCU) Lahore. He received his MS degree from National University of Sciences and Technology in 2009. His area of interest is ontology alignment, e-learning and semantic activity recognition.

Rana Faisal Munir is Research Scholar in University of Catalan Spain and working on domain of quality control for e-learning systems.

Affiliations

Sohail Sarwar[1] · **Zia Ul Qayyum**[1] · **Raúl García-Castro**[2] · **Muhammad Safyan**[1] · **Rana Faisal Munir**[3]

Zia Ul Qayyum
zia.qayyum@uog.edu.pk

Raúl García-Castro
rgarcia@fi.upm.es

Rana Faisal Munir
fmunir@essi.upc.edu

1 Department of Computing, University of Gujrat, Gujrat, Pakistan

2 Universidad Politecnica de Madrid (UPM), Madrid, Spain

3 Universidad Politecnica de Catalan, Barcelona, Spain