Intelligent Recommendations for e-Learning Personalization Based on Learner's Learning Activities and Performances

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Daminda Herath
University of Colombo

Intelligent Recommendations for e-Learning Personalization Based on Learner's Learning Style and Performance

Daminda Herath, Laxman Jayarathne
University of Colombo School of Computing, Colombo, Sri Lanka.

ABSTRACT

Recommendation systems are widely used in many fields such as e-commerce. Recently, researchers have adapted this approach in e-Learning environment to recommend resources (e.g. papers, books, hyper-links, and hypermedia) to the learners. In this paper, we present the intelligent recommendations for e-Learning personalization approach which uses recommendation techniques for educational data mining specifically for identifying e-Learners' learning styles, monitoring, predicting performance. Recommended learning resources are computed based on the current learner's navigational patterns, exploiting similarities and dissimilarities among learners' preferences, educational contents, results obtained in various practical's, exercises and interactions with different activities. The proposed framework for intelligent recommendations for e-Learning environment is composed of three modules, a learner module which uses to identify learners' learning styles, a domain module which contains all the knowledge for particular discipline and a recommendation module which pre-processes data to build a relevant recommendation lists and predicting performances. Recommended resources are obtained by using level of knowledge of learners in different stages and the range of recommendation techniques based on content-based filtering and collaborative approaches. Several techniques such as classification, clustering, predictions, association rules are used to enhance personalization with filtering techniques to provide a recommendation and encourage learners to improve their performance.

Keywords: *E-Learning, Learning Style, Educational Data Mining, Content-Based Filtering, Collaborative Filtering.*

1.0 INTRODUCTION

With the rapid growth of the Internet, e-Learning systems are efficiently used for education and training in academic and non-academic places. However, most of e-Leaning systems have not been personalized, several works have addressed the need for personalization in e-Learning domain. Most of current e-Learning systems are still delivering the same educational resources in the same way to learners with different profiles [1].

In general, to enable personalization, existing systems use one or more type of knowledge (learners' knowledge, learning materials knowledge, learning process knowledge, etc.) and personalization in e-Learning systems concern adaptive interaction, adaptive course delivery, content discovery and assembly, and adaptive collaboration support. The category of adaptive course delivery presents the most common and widely used collection of adaption techniques applied in e-Learning systems today [1].

Therefore, personalization plays a significant role in adaptive e-Learning system. This needs learner profile due to different preferences, learning styles among learners. Due to huge amount of learning resources on the web, it is hard to find learning resources related to learner request [2].

Recommendation system is an application capable of presenting a user a suggestion for an object, obtained on the basis of his previous preferences and the preferences of a community which has likings and opinions similar his/her. Therefore, recommendation systems help learners to reduce the overload of information that they suffer nowadays, providing, at same time, customized access to information for a specific domain [3]. In that case, recommendation systems motivate learners to improve their performance as well as.

Current e-Learning systems are not providing a better facility to track the learner's progress. It leads learners less interaction with e-Learning system or keep out from e-Learning. This paper proposes a system with intelligent recommendations for e-Leaning personalization based on learners learning style and performance. It means personalization approach for providing learning resources for active learners in e-Learning system. This system recommends some learning resources (learning objects, articles, videos, event details etc.) based on learner's level of knowledge, learner's profile and some other learner's activities). Also the system provides a facility to track learner progress based on practical tests and exercises (assignments) and monitor the learner's performance in order to guide and support the learners.

2.0 BACKGROUND OF RESEARCH

Current e-Learning systems have several following problems. The first problem is the amount of time spent searching for right content [2]. Learning can be taken place at any time and place. However, with the increase of learning resources, it is a time-wasting effort for learners to access desired and suitable resources.

In addition, there is an inadequate search technique for searching the learning resources [2]. In order to solve this, educational data mining techniques are used to enable an implementation that is open, scalable and fast to deploy [1].

Another problem is the absence of personalization in current e-Learning system [2]. Learners with similarity learning styles have the similar learning resources, even though, they have dissimilarity learning styles. Learning profiling for all learners can solve this problem. Since learner model is created for every learner. The system will recommend learning contents based on the model [2].

Another problem is to offer appropriate learning resources to the right learner in a correct way [2]. The proposed system can solve this problem by implementing the content-based and collaborative filtering approaches. In content-based filtering the e-Learners are recommended relevant web contents that are similar to the once they preferred or accessed or liked in past. Collaborative filtering, the e-Learners are recommended relevant web contents that are similar to the other e-Learners' preferred or accessed or liked in past [5][6]. These approaches are named information filtering which uses resources to learners. Both of these approaches work based on "rating" or "preference" system [2].

However, both content-based and collaborative filtering suffer cold-start problem. This problem happens in cases where there is a lack of information about e-Learners and their preferences in past which makes it impossible to provide relevant recommendations [6][7]. Another limitation of collaborative filtering that it needs a community of learners who know each other. Thus, collaborative filtering is unable to recommend anything. Content-based filtering considers to one learner, so the results are not sharable [2]. To overcome the problems with information filtering, the proposed system is going to introduce different level of questionnaires to identify initial level of knowledge of the learners.

Predicting learner performance and tracking the progress are another challenges in current e-Learning system [8]. Learners take different type of practical, skill and assignment tests to continue their learning process in order to gain knowledge. But current e-Learning systems are lacking of predicting facility, even learner cannot check the progress as well as. To address these issues, regression method is used to predict results and subsystem is introduced to check progress of each e-Learners based on above mention method.

The proposed system helps learners to choose and find learning resources they want to learn. Learner's learning style such as leaner's history, navigational pattern, preferences, knowledge level, results of practical, skill level, assignment tests and various activities are stored in learner profile. Learner profile will be updated by the system dynamically based on relevant interactions on relevant interactions by learner through the system. Then the system will evaluate learner's preference. Finally learners are interacted with system using friendly interfaces.

3.0 LITERATURE REVIEW

The personalization in e-Learning process has been widely discussed in the past decades and remain the focus of attention of many researchers today.

Bourkoukou et al. [7] proposed a personalized E-learning system, which takes the learner's personality into account and uses collaborative filtering method for the recommender system. In this model some modules for personality recognition and selecting an appropriate learning scenario for learner's personality are presented.

In another research, Essaid et al. [9] proposed a personalized e-learning system LearnFit which can which takes the dynamic learner's personality into account. In this system some modules for personality recognition and selecting appropriate teaching strategy were used to achieve the learning.

The results indicate that placing the learner beside an appropriate teaching style matching with learner's preference led to improvement and made the virtual learning environment more enjoyable.

Thai-Nghe [8] proposed a novel approach which uses recommender system techniques for educational data mining, especially in predicting student performance. They also proposed how to map the educational data to user/item in recommender systems. To validate this approach, they compared recommender system techniques with traditional regression methods such as logistic regression by using educational data. Experimental results showed that the proposed approach can improve the prediction results.

In this research, KHRIBI et al. [4] described a fully automatic learner modeling approach in learning management systems, taking into account the learners' educational preferences including their learning styles. They proposed a composite learner model made of three components: the learner's profile, learner's knowledge, and learner's educational preferences. The learner's profile represents the learner's general information such as identification data, the learner's knowledge captures the learner's interests on visited learning objects, and the learner's educational preferences are composed of the learner's preferences (in terms of the specific attributes of the visited learning objects) and his/her learning style. In the proposed approach, all the learner model components are automatically detected, without requiring any explicit feedback. All the basic learners' information is inferred from the learners' online activities and usage data, based on web usage mining techniques and a literature-based approach for the automatic detection of learning styles in learning management systems. Once learner models are built, the proposed system applied a hierarchical multi-level model based collaborative filtering approach, in order to gather learners with similar preferences and interests in the same groups.

4.0 RESEARCH METHODOLOGY

Generally, intelligent recommendations for e-Learning personalization system consists of three main components, Domain Model, Learner Model, and Recommender Model.

Fig. 1 shows the overall architecture of the proposed system.

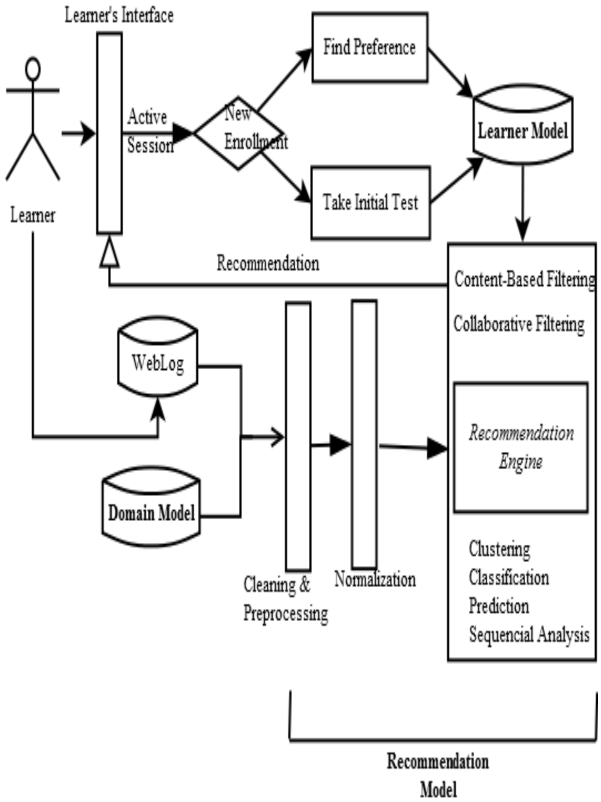


Fig. 1 – The Overall Architecture of the Proposed System

A. Domain Model

A domain model contains the knowledge about the curriculum structure. This model is split into three layers, the first represents the course and each course is divided on several concepts, and each concept is presented by a set of learning objects.

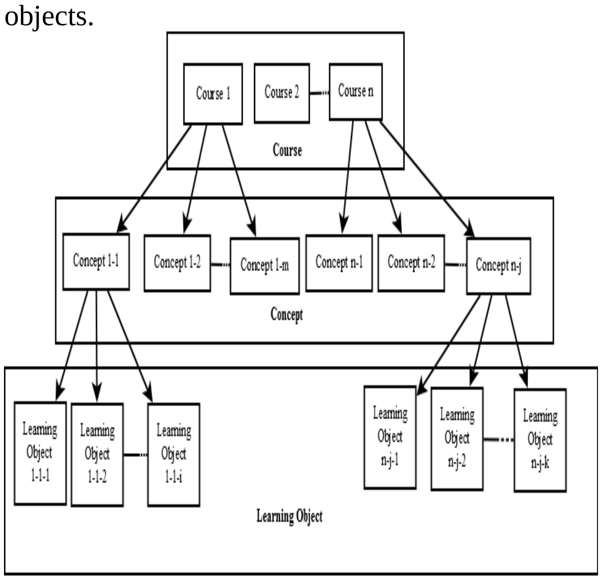


Fig. 2 – Hierarchical Organization of the Domain Model

A learning object holds one unit of knowledge and presents different aspects such as lecture notes, presentations, questions, activities, examples, exercises etc. [9]. In this research, “Introduction to Python Programming” course has been selected to explain course structure as below table 1.

Table-1: Introduction to Python Programming Course structure

Course : Introduction to Python Programming	
Concept 1: Introduction to Python	
Learning Object 1	Overview of Python
Learning Object 2	Basic Syntax
Learning Object 3	Variables and Data Types
Concept 2: Operators and Expressions in Python	
Learning Object 1	Types of operators
Learning Object 2	Operators precedence
Concept 3: Selection Control Structure in Python	
Learning Object 1	if, if else and Multi-way selection
Learning Object 2	Nested selection
Learning Object 3	Exception Handling
Concept 4: Selection Control Structure in Python	
Learning Object 1	The for loop
Learning Object 2	The while loop
Learning Object 3	Nested loop
Learning Object 4	break and continue
Concept 5: List,Tuple,Dictionary, Number and String	
Learning Object 1	Lists
Learning Object 2	Tuples
Learning Object 3	Dictionaries
Learning Object 4	Number
Learning Object 5	String
Concept 6: Functions	
Learning Object 1	Defining and Calling a function
Learning Object 2	Function Arguments
Learning Object 3	Return Statement
Learning Object 4	Scope of variables and The anonymous functions
Concept 7: Handling Files I/O	
Learning Object 1	Reading keyboard Input
Learning Object 2	Opening and Closing files
Learning Object 3	Reading and Writing files
Learning Object 4	File and Directory Handling

Each course includes different level of tests to identify the learner level of knowledge. Each level of test has a set of questions. Those questions have different types of proficiency levels. Table 2 and Table 3 describe the test structure and proficiency with allocated energy points.

Table -3: Test Structure

Test Name	**No of Test per Course**	**No of Questions per Test**	**No of Attempts**
Initial Skill	No of concepts per Course (nCn)	nCn * 5	1
Practical	No of Learning Objects per Course (nLo)	nLo * 5	any
Final Skill	No of concepts per Course (nCn)	nCn * 10	Maximum 2
Assignment	1	nCn * nLo * 5	1

Table -3: Proficiency with allocated Energy points

Proficiency	Energy Points
Very Hard	30
Hard	25
Medium	20
Easy	15
Very Easy	10
Total	100

B. Leaner Model

The learner model represents the various characteristics of the learner such as personal information, preferences, navigational patterns, accessed contents, level of knowledge, etc. which can be used to generate an individualized learning experience [7]. In our research, learner who enroll with a particular course is going to take questions (Initial skill level test) to determine the initial level of knowledge and build the learner profile. Apart from that, learner preferences are used to present the learner profile as well as [9].

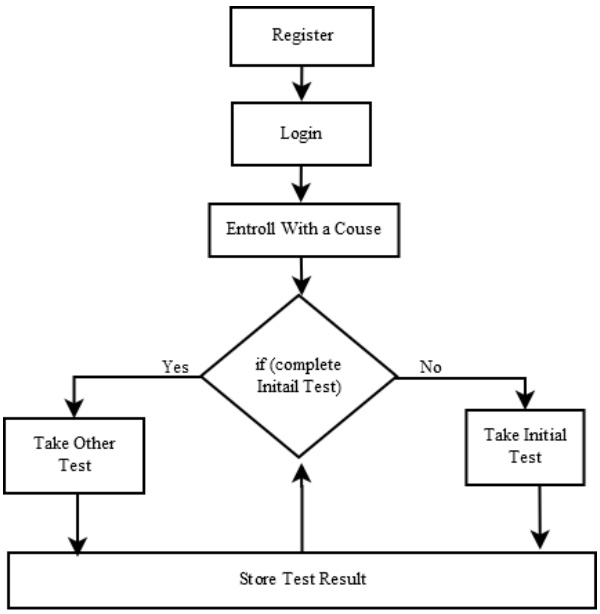


Fig. 3 – A Flow Chart for Learner Interaction with Initial Skill Test

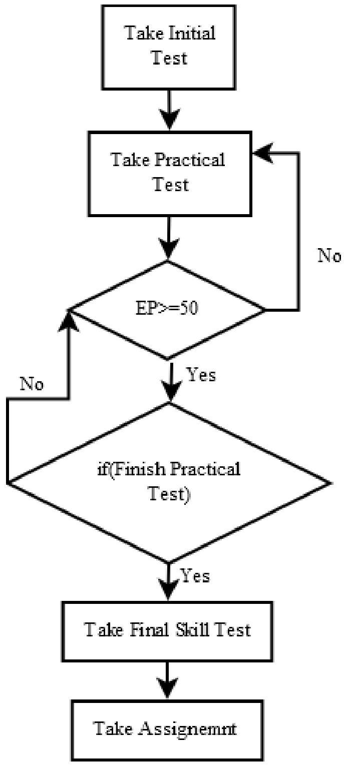


Fig. 4 – A Flow Chart for Learner Interaction with different Tests

C. Recommendation Model

The proposed recommendation model has two modules, respectively 1) intelligent recommender module and 2) prediction module. In intelligent recommender module, if it is a new learner, the proposed system invites the learner to take initial skill level test in order to build learner profile based on learning style. Once the learner completes the initial test, the result is stored in learner model and then system generates the recommendation list for specific learner based on the result. Then the learning process can be started, we can overcome cold-start problem in recommendation system. A common problem in recommender systems is the cold start problem. It occurs when the new user is logged into the system. Due to lack of ratings of the new user, it is impossible to calculate the similarity between her/him and other users and thus the system cannot make accurate recommendations [10].

Once the learner interacts with the system, data mining techniques use to collect information about learner's learning styles such as navigational patterns, preferences, accessed contents, bookmarks etc. to build learner profile and to generate intelligent recommendation. In this module, there are four steps to follow such as cleaning and preprocessed, Normalization, Similarity Computation and Recommendation [7].

The intelligent recommender module helps to generate suitable recommendation to learners based on learning style. This module uses content-based filtering and collaborative filtering to do that. First we apply the content-based filtering approach, the term vector is submitted in order to compute recommendation list. Results are ranked according to the cosine similarity of their content (vector of TF-IDF weighted terms) with submitted term vector. Second, we apply the collaborative approach in order to classify the active learner in one of the learner's group [1].

D. Recommendation Process

Learners' initial preferences tend to be noisy. Hence relevant courses/Articles/Videos should be extracted from them. To do this, it is important to apply mathematical functions to them so that items can be selected based on some criteria, such as similarity, hence we use vector space model to represent learner's initial courses/articles/videos preferences.

Vector Space Model (VSM) is used to represent documents in a multi-dimensional algebraic manner to apply mathematical functions to the document. It represents a document as a vector. The vector is capable of containing sub-vectors within it. Each attribute of the document is considered as an individual vector. In the context of the given problem of the research, an item (course/article/video) is considered as a vector, and its attributes such as keywords/learning objects will be sub-vectors. Each item is considered as a point in the vector space and it assumes that the most relevant or similar items are the nearest ones. To compare a/an course/article/video, their relevant sub vectors are compared with each other and similarity measured using Cosine Similarity and TF-IDF weights. Therefore, we adapt the same Vector Space Model into our research [11].

Time Frequency (TF) can be represented as $tf_{t,d}$ is the frequency of a particular term t within a given document d. The equation for TF weight is as follows.

$$w_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{tf}_{t,d} & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Document Frequency (DF) gives the number of documents that contain a particular term t and is represented as df_t . Inverse Document Frequency (IDF) on the other hand reduce the prominence of highly used terms and gives an important to less frequently used items as well.

$$idf_t = \log_{10}\left(\frac{N}{df_t}\right) \quad (2)$$

TF-IDF weight is the product of both TF and IDF weights and provides the term specific weight of the system and this value is used in obtaining the Cosine similarity.

$$\boxed{w_{t,d} = (1 + \log tf_{t,d}) \times \log_{10}\left(\frac{N}{df_t}\right)} \quad (3)$$

Cosine similarity provides means of calculating the similarity between two vectors. We can leverage it to compute the similarity between two courses based on a particular feature p. As we use TF-IDF weights in calculating the Cosine similarity, the learner profile will contain a reasonable amount of similarity as well as diversity and thereby by solving the overspecialization issue.

$$sim^p(\vec{m}_i, \vec{m}_j) = \frac{\vec{m}_i \bullet \vec{m}_j}{|\vec{m}_i| |\vec{m}_j|} = \frac{\vec{m}_i}{|\vec{m}_i|} \bullet \frac{\vec{m}_j}{|\vec{m}_j|} \quad (4)$$

$$= \frac{\sum_{n=1}^{t} w_{n,i,p} \cdot w_{n,j,p}}{\sqrt{\sum_{n=1}^{t} w_{n,i,p}^2} \cdot \sqrt{\sum_{n=1}^{t} w_{n,j,p}^2}}$$

$\vec{m}_i$ *- item i,*

$w_{n,i,p}$ *- tf-idf weight of item i based on attribute p*

$\vec{m}_j$ *- item j,*

$w_{n,j,p}$ *- tf-idf weight of item j based on attribute p*

By comparing the similarity of every course in the learner's the initial preference list with the rest of the courses in the same list, we can find out what are the courses that give the highest similarity value with the TF-IDF weighting scheme. Out of the items in the learner's initial preference list, top 10 items will be added into the learner profile. Therefore the courses in the learner profile contain a reasonable amount of similarity [11].

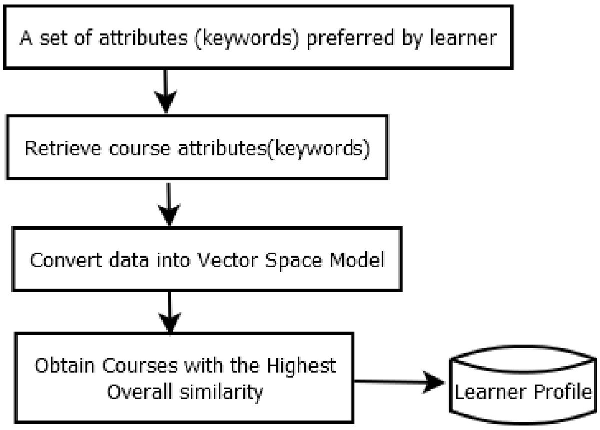


Fig. 5-Creating a Learner Profile

E. The Utility Matrix

Recommendation systems deal with users and items. A utility matrix offers known information about the degree to which a user likes an item. Normally, most entries are unknown, and the essential problem of recommending items to users is predicting the values of the unknown entries based on the values of the known entries [12].

Example 1. After weighting courses with keywords, we obtained a Course-Keyword Matrix with n rows in which n denotes number of courses $C=\{c_1,c_2,c_3,\ldots.c_n\}$, and m columns denotes the number of keywords $K=\{k_1,k_2,k_3,\ldots.\ k_m\}$.

Table-4: Course-Keyword Matrix

	k_1	k_2	k_3	k_4	k_5
c_1	0	0	0	1	1
c_2	1	1	0	0	0
c_3	1	0	1	0	0
c_4	1	1	1	0	0

The number of times an attribute value occurs within a single item, can only occur once (1) or not occurs at all (0).

Example 2. After weighting learning resources, we obtained a preference model for each learner defined as a Learner-Learning Object Rating Matrix with n rows in which n denotes the number of learners $L=\{l_1,l_2.....l_n\}$,and m columns denotes the number of learning objects $J=\{j_1, j_2, \ldots., j_m\}$.

Table-5: Learner-Learning Object Rating Matrix

	j_1	j_2	j_3	j_4	j_5
l_1	4	0	1	4	3
l_2	2	1	0	0	0
l_3	4	0	2	2	3
l_4	5	4	4	0	0

This matrix use a 0-to-5 rating scale where: 5 means that the learner is strongly satisfied with the selected learning object, 1 indicates that the learner is not at all satisfied with the learner object, and finally the score 0 indicates that the learning object is not yet explicitly rated or used at all [7].

Finally, prediction module in recommendation model predicts future results for the different tests. Learners can check progress individually and compare with other learners. To implement prediction module, the system is used liner regression algorithm.

5.0 EXPERIMENT RESULTS

In order to implement and evaluate the proposed personalization approach, we used “Introduction to Python Programming” course as a prototype. We selected a set of students who is following Bachelor of Degree in Information Technology at University of Colombo School of Computing to determine learning styles and performances. Those students had a little or lack of knowledge about python programming.

The results show that performance of students improves significantly as progresses in above mentioned course and also their learning activities were high during the studies. The following figures show the relevant evidences such as learner’s individual performance, recommendations list based on the learner’s interactions, result prediction of the learner, learner’s activities, learner’s login frequency etc. Finally it shows the comparison with other learners as well as.

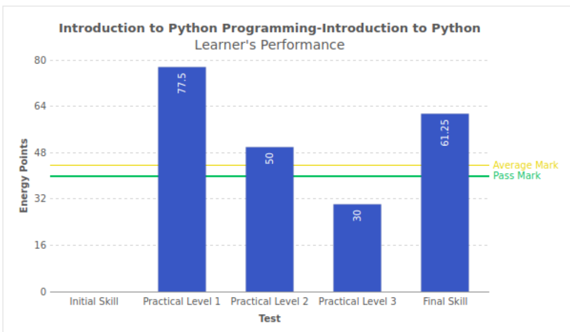


Fig. 6 - learner’s individual performance based on Introduction to Python Concept

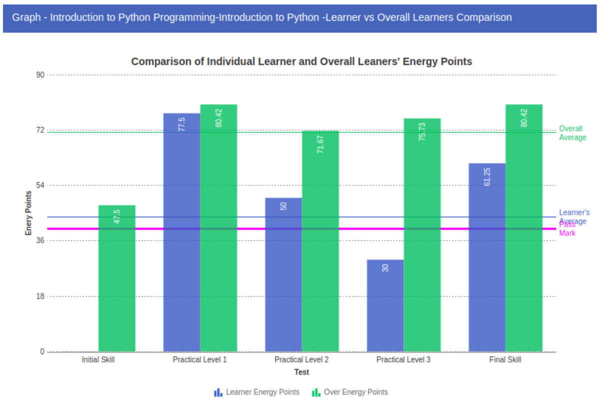


Fig. 7 - Comparison of Individual Learner and Overall Learners' Energy Points based on Introduction to Python Concept

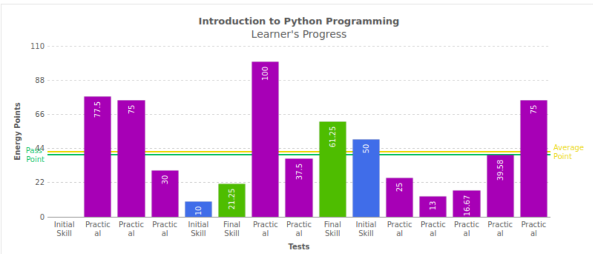


Fig. 8 – Learner's Progress in Introduction to Python programming Course

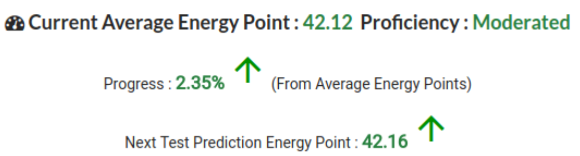


Fig. 9 – Learner's Next Result Prediction

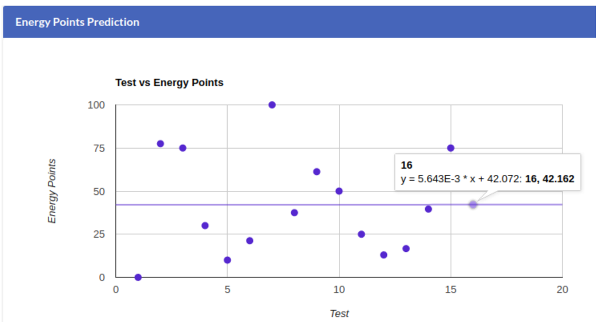


Fig. 10 – Learner's Energy Points Scatted plot in Introduction to Python programming Course

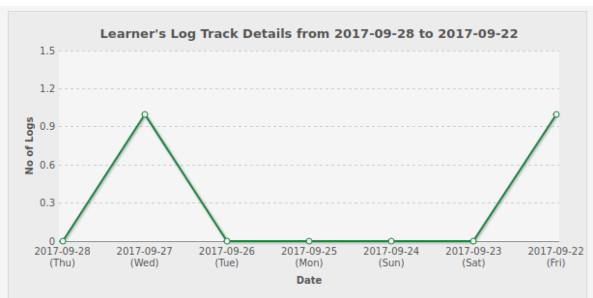


Fig. 11- Learner Login Frequency

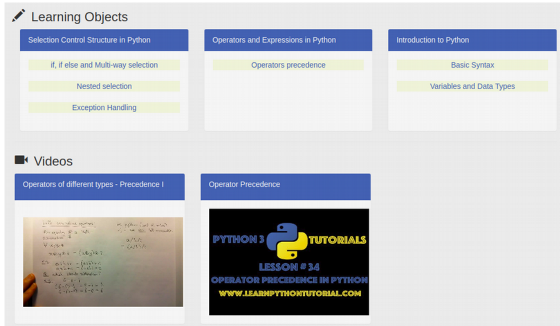


Fig. 12 – Given Recommendations to Learner

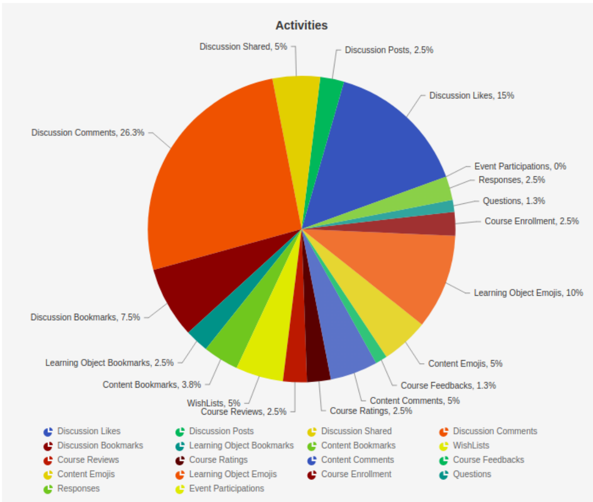
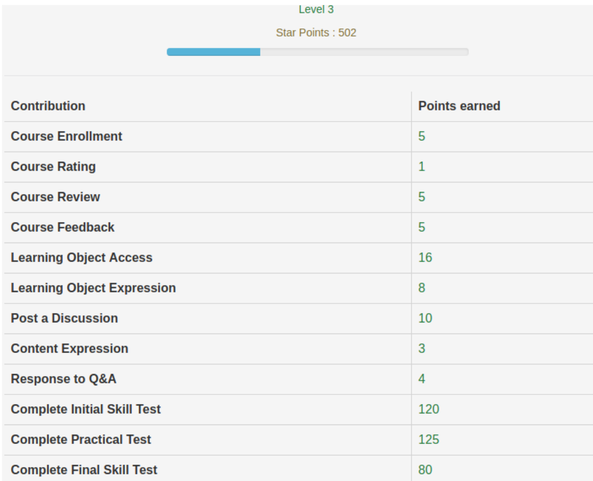


Fig. 13– Learner's Activities



Level 3

Star Points : 502

Contribution	Points earned
Course Enrollment	5
Course Rating	1
Course Review	5
Course Feedback	5
Learning Object Access	16
Learning Object Expression	8
Post a Discussion	10
Content Expression	3
Response to Q&A	4
Complete Initial Skill Test	120
Complete Practical Test	125
Complete Final Skill Test	80

Fig. 14- Learner's Earned Points

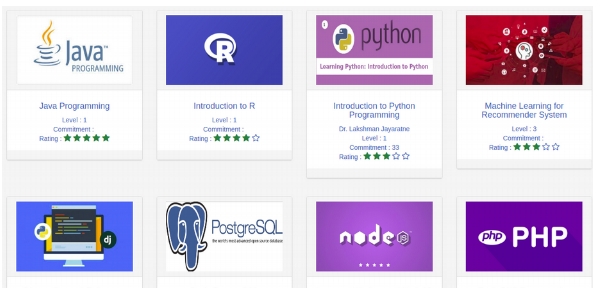


Fig. 15- Interface to access courses

The analysis reveals that the average energy points in initial skill level attempt in each quizzes of the concept are lower than the average energy points in other tests. It is due to the reason that the initial skill level attempt of quiz was started with zero or beginning level of knowledge of the learners. Then the system recommended suitable learning objects, articles videos to repeat the lesson and improve their knowledge based on their individual performance and other learners' performances. Practical tests are provided to fine tune learner's knowledge about referred learning resources in a systematic way. The process continued till learner achieved acceptable energy points in final skill level attempts. Finally learner had to take assignment quiz to evaluate the final result.

During the e-Learning process, system encouraged the learners to participate different activities such as taking various quizzes, discussing topics, rating, reviewing, adding bookmarks etc. to and earn points. Figure shows the earned points individually by learner. Therefore, this point indicator motivated the learner to interact with the system more and more.

6.0 FUTURE WORKS

In future work, we will develop an academic repository of different learning resources with question data bank to create more adaptive and adaptable e-Learning environment.

7.0 CONCLUSION

E-Learning environment plays an important role in today's education. As the amount of learning recourse becomes very large, providing personalized resource recommendation is a significant functionality for today's e-Learning systems. Therefore, the recommendation systems are one of the best tools to deal with the problem of overload information which will help users to find optimal interested items.

We proposed the intelligent recommendations for e-Learning personalization system, which takes the learner's learning styles into account and uses content-based filtering, collaborative filtering and educational data mining methods for recommendations and predications. Here, we try to overcome the cold-start problem by introducing initial skill level test to determine initial profile of new learner.

In this research, the system evaluate learner's level of knowledge, learner's learning styles and leaner's performances. Then, the system presents recommendation list according to the results of learner's evaluation and profile.

In order to evaluate proposed system, we implemented a prototype among selected learners. Results show that using the proposed approach could improve performance of learners significantly.

8.0 ACKNOWLEDGMENT

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