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An E-learning recommender system using switch hybridization

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Abstract
A recommender system is developed to improve the efficient performance of new learners using stereotype filtering and collaborative filtering. The paper aimed at adopting a model that follows a classification of recommendation based on information sources that are being used, such as user profile and user-item profile to make accurate recommendation to new learners. The system undertakes stereotype filtering because it is less sensitive to the new learner. In stereotype filtering, recommendations are issued to new user by first identifying the category they belongs to and locating preferences of other users in the same category. The proposed system combines both recommendation techniques in order to gain better performance and address the shortcomings of each. The result showed that the satisfaction level are based on learner academic Information. Privacy issues should be explored in gaining learner's loyalty as well as frequent feedback. Hence, there is need for developing additional facilities to preserve privacy information and at the same time be able to use them for accurate recommendation.

Keywords: collaborative filtering, E-learning, recommender system, switch hybridization, stereotype filtering

Introduction
Lately the conventional method of classroom education is evolving to new method i.e. e-learning method. Students face challenge by having difficult time in choosing few courses that will be relevant and provide a timely improvement on their performance. Even it is difficult for students to locate courses that might best fit their individual area of specialization which lead to loss of learning motivation, frustration and stress among student. E-Learning is a growing methodology of modern education. Most tertiary institutions such as University, Polytechnics, College of Education, Innovative Colleges etc. as well as companies started offering online courses to meet the student needs, and to improve employee performance. It also provides base for strong research, path for communication, mobility, personalized learning etc. It provided classes likes recorded lectures, E-Books, Blogs, Wikis etc. E-learning systems help learners to learn electronic course through computer or network as virtual classroom instead of face-to-face learning. This type of learning has some advantages versus conventional learning system. Face to face learning or conventional learning systems will be time consuming for the learner and also learner should spend more cost in contrast with the learning as virtual classroom (Yu, 2007) [7].
Institutions have been seeking for ways to improve learner(s) efficiency and performance. E-learning brings benefits to the learner by making access to relevant educational resources very fast and just-in-time at any time or place (Ghaleb, & Hasna, 2006) [3]. The arising challenge with the existence of such huge amounts of learning resources is how to recommend relevant or fittest learning resources to learners when they have limited time to view and study all of them. Recommendation systems proved to be the appropriate solution of the above discussed problem. Among the popular approaches used in recommender systems are the using of either a collaborative filtering or a content-based filtering technique. Collaborative filtering identifies the interesting items from other similar users' opinions by calculating the nearest-neighbour from a rating matrix. New items that are of interest to the nearest neighbour and that have not been rated by other users with similar interest will be recommended to them. System cannot provide reliable recommendation for a new user because few or no ratings are available. In contrast, content-based filtering uses attribute of items to infer recommendations. Hence, items with similar content to the current viewing item will be recommended to the active user.

Designing a personalized recommendation system for learners incorporate having the awareness of our target group of learners. For instance, movielens.org (a well-known recommendation system for movies) demands new users to rate a specific number of movies before the system is able to provide personalized recommendations based on the movies that the user liked in the past. Such an initial data set is needed to solve the so-called 'cold start' problem (Al Mamunur, Cosley, Lam, McNee, Konstan, & Riedl, 2002) [1].

Researchers have found that collaborative filtering have the unique capacity to identify cross-genre niches and can entice users to jump outside of the familiar. However, the cold-start problem has the side-effect of excluding casual users from receiving the full benefits of collaborative and content-based recommendation (Robin, 2007) [6]. Damien, Liao, Njagi and Kagorora (2015) [2] proposed a new method for paper recommendation which is based on similarity of specific fields of both the target paper and candidate paper (Title, abstract, introduction and related works sections) and uses cosine similarity function to measure the relevance. They also proposed an academic researcher papers recommendation approach that is based on the paper's topics and paper's main ideas. The approach requires as input only a single research paper and extracts its topics as short queries and main ideas' sentences as long queries which are then submitted to existing online repositories that contains research papers to retrieve similar papers for recommendation. Four query extraction and one paper recommendation methods are proposed.

Ristoski, Mencía and Paulheim (2014) [5] addressed the challenges of building hybrid recommender systems that use linked open ratings data from different databases. A hybrid multi-strategy approach was used to combines the recommendation results of different base and generic recommenders using stacking regression and rank (ratings) aggregation for producing a final recommendation. Even though they were able to generated ratings popularity scores for recommendation generation, they however failed to explore the use of demographic recommenders.

Jajvand, Seyyedi, & Salajegheh (2013) [4] proposed an approach that was yielded to overcome the problem of grey sheep, new consumer, and new service entrance to Collaborative Filtering Recommender system. The recommender system uses the switching hybrid method, and combines two methods of collaborative filtering and context-aware.

Methodology

Methodology involves implementing and evaluating a recommender system with e-learning domain based on the scope of the paper. Different kind of recommender system algorithms were implemented and evaluated. Thereafter, the system produced collaborative filtering and Learner demography filtering recommendation.

Describing the learning interest and status of learners is the first and vital step of e-learner community building. A learner must register before he/she can be able to get personalize recommendation from the system.

The personal detail such as stereotype data, login information and users interest will be captured during registration. User can only be registered if having a valid username and password in order to login. The system provides course recommendation based on stereotype filtering and collaborative filtering.

In stereotype filtering, prior knowledge on demographic information like area of specialization, interest of learner and the opinion for recommendation. It's based on the assumption that learners belonging to a certain demographic group have similar preference. The system uses clustering technique to classify learners into different demographic groups. Consequently, regarding the present situation of the learner and without the necessity of the rate history, the learner receives a recommendation.

Recommendation technique can be distinguishing on the basis of their knowledge sources. The switching hybrid method starts the recommendation procedure with selecting one of the available recommender systems regarding selection criteria. When the appropriate recommender system is selected, the other recommender systems will not play any role in the recommendation process. The merit of switching is that it can be sensitive to the strength and weakness of its constituent recommenders.

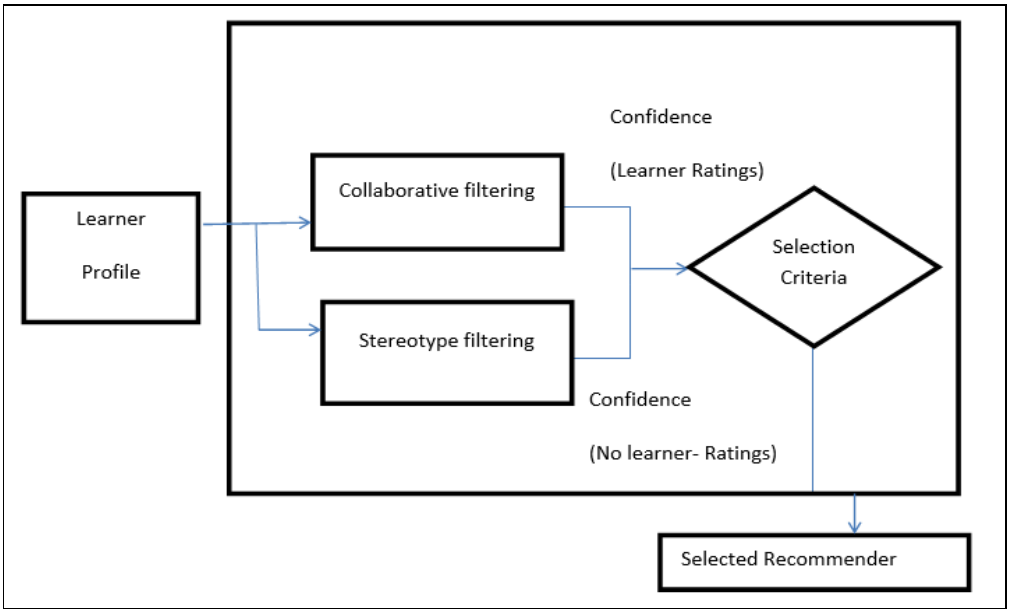

Fig 1: System Architecture

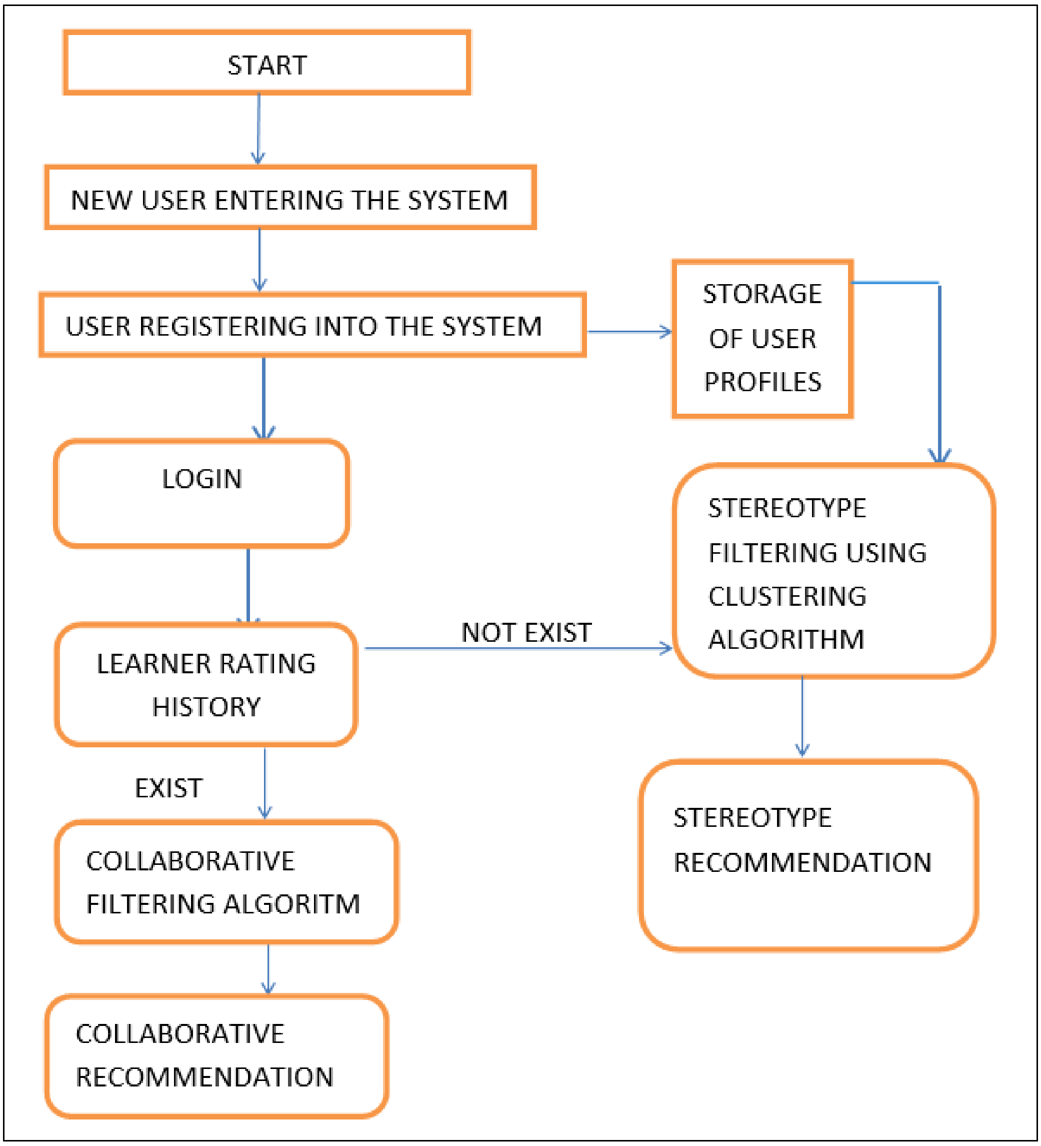

Fig 2: Recommendation Technique

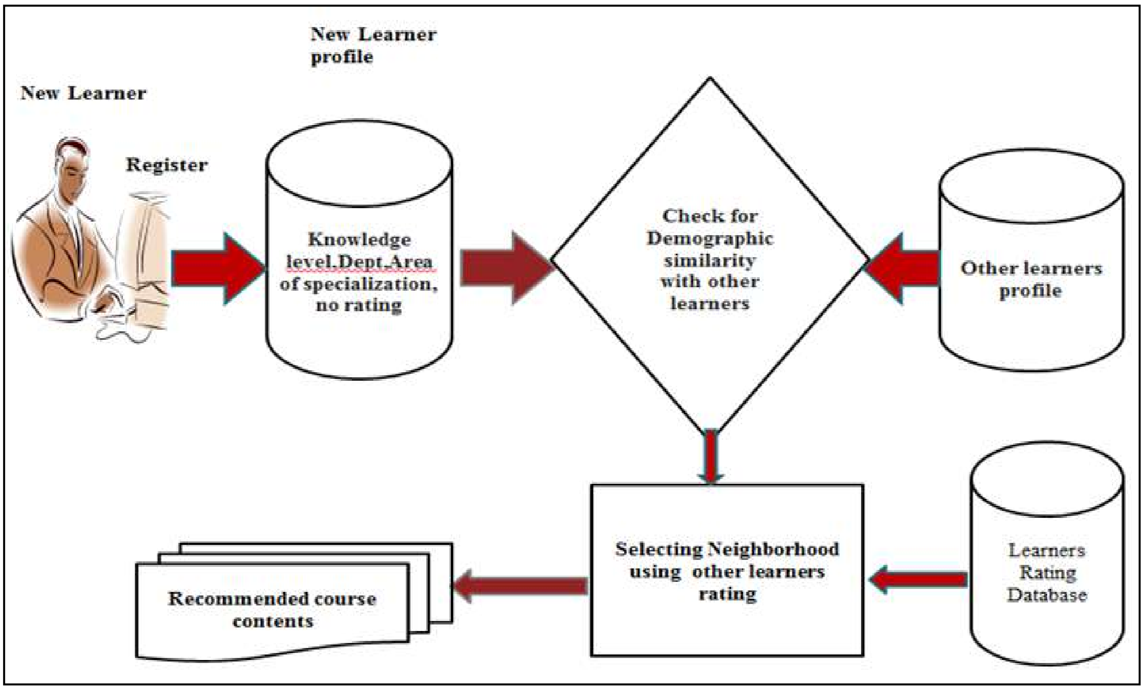

Fig 3: Demographic or stereotype filtering

The system starts with registering each new learner. The registration data are stored in the learner profile. Then according to the learner profile the learner is assigned to the appropriate group. The data stored in the learner profile are entered by the users during the registration process. The learner data are reduced to only few attributes of demographic information and one that characterizes learner's interests.

When a learner registers and provides demographic information, the learner will be grouped into the cluster that best fits the learner's demographics. These clusters will be predefined. Similarities will then be found for the learner and other learner in the cluster for recommendation provision to the learner. Furthermore, the specific courses assigned to the cluster for recommendations will be recommended to the learner.

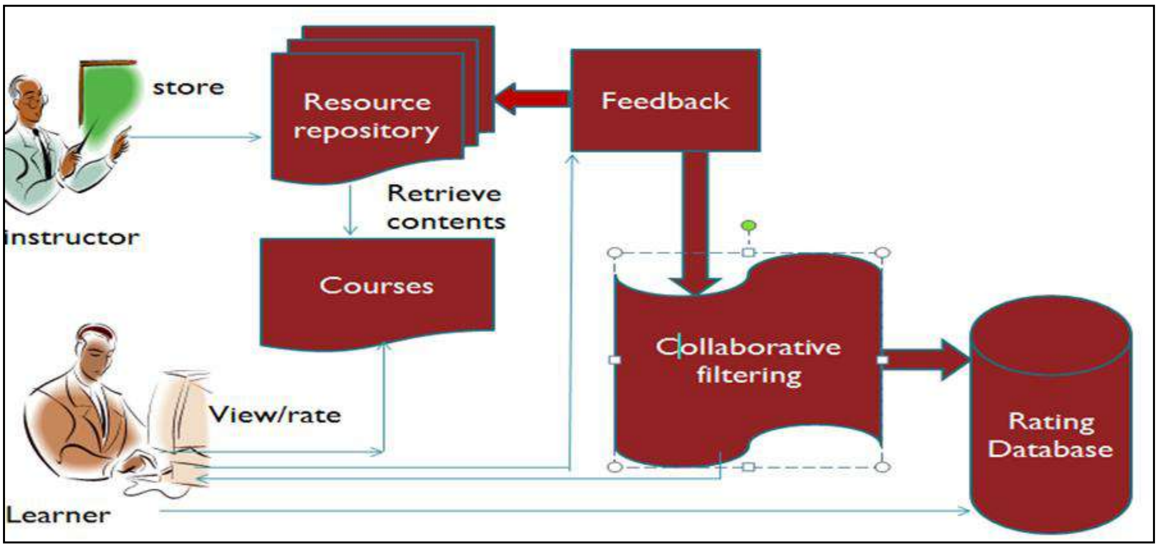

Fig 4: Collaborative Filtering

Collaborative Filtering Technique

K-Nearest Neighbor Algorithm

K-Nearest Neighbor is a supervised learning algorithm, which is the most popular method used for classification, estimate, and prediction.

This algorithm is to classify learners and give predictions for courses. The idea is to find other learners whose past ratings for courses are similar for the active learner and use their ratings to predict current learner's preference for a course he/she has not rated.

The measurement for the weight for similarity between two learners *i, p* is the Pearson correlation coefficient

$$w(u,v) = \frac{\sum_{j}^{m}(r_{u,j}-\bar{r}_u)(r_{v,j}-\bar{r}_v)}{\sqrt{\sum_{j}^{m}(r_{u,j}-\bar{r}_u)^2}\sqrt{\sum_{j}^{m}(r_{v,j}-\bar{r}_v)^2}}$$

In the above equation,

j is the set of items rated by both users, m is the set number of collaborative users

r_u and r_v denotes average of learner u's and v's ratings

$r_{u,j}$ and $r_{v,j}$ denotes learner u's and v's ratings for item j

Conditions for selecting Neighbors

W (u, v) denotes how much learner u tends to agree with learner v on the item that both learners have already rated.

Step 1: If the learners do not correlate each other. Then w (u, v) = 0. Since w (u, v) is equal to zero, this is the switching criteria because there is sufficient confidence that there is no similarity between the active or new learner and others. So stereotype filtering technique is attempted

Step 2: If the learner i and v have a similar rating for an item then w (u, v) > 0

Step 3: Since the algorithm generate some similarity between users then finally, compute the prediction for new or active learner u on item k.

To generate prediction or recommendation for learner u, KNN uses similarity to select a neighborhood N E L of u. Once neighborhood N has been selected, the ratings of learners in neighborhood N is combined by the recommender system to generate prediction for learner u's preference for an item I.

Prediction function

$F_{u,i} = r_u + g *(\sum w(u,v) * (r_{v,k} - r_v))$

The prediction function F, calculates the prediction of target user u for item i.

M is the total numbers of collaborative users then multiplies by the rating difference of sub-item i. then sum it up and multiply by the modulation factor g and added with the average rating r_i of our target user which will give the prediction rating of our target user recommendation.

Stereotype filtering Technique

K-Means Clustering Algorithm

Learners are partitioned in different cluster using k-means clustering algorithm by using user's demographics. Ratings are computed in the following stages:

1. Similarity of active's user's demographics is calculated from all clusters. Pearson correlation is used as similarity measure. High similarity value indicates the cluster for target learner.

2. Rating for target user is given by multiplying similarity measure with average rating of cluster in which target user lies. The system starts with registering each new learner. The registration data are stored in the learner profile. Then according to the learner profile the learner is assigned to the appropriate group. The data stored in the learner profile are entered by the users during the registration process. The learner data are reduced to only few attributes of demographic information and one that characterizes learner's interests.

Result and Discussion

The recommendation system was develop to provide accurate prediction of what learners might get when finding elective courses of interest in various area of specialization. The recommendation system was developed to improve the performance of leaner by hybridizing stereotype filtering with collaborative filtering to solve new user cold start problem. Our system was developed by using glassfish server and wampp server.

Fig 5: Learner's Login Page

Figure 5 depict the learner's login page. This page allows leaners to gain access to system by supplying their login details that must have been created during registration. When a learner logs in, the system check if the login details provided and rating history are available in the database, if so, it will switch to existing learner's account. If not, it will switch to new leaner registration page. The registration page for new learner allow them to register by supplying their name, gender, department, area of specialization, matriculation number, level, email address. Figure 6 shows registration page for new user to fill the form above and get course recommendation based on their attributes like area of specialization, level and department.

Figure 7 depicts the recommendation section is empty simply because no existing learner having the same area of specialization and level with the new user has rate any course. It shows the key meanings for each rating values.

Fig 6: New Learner's Sign up Page

Fig 7: Recommendation Page A

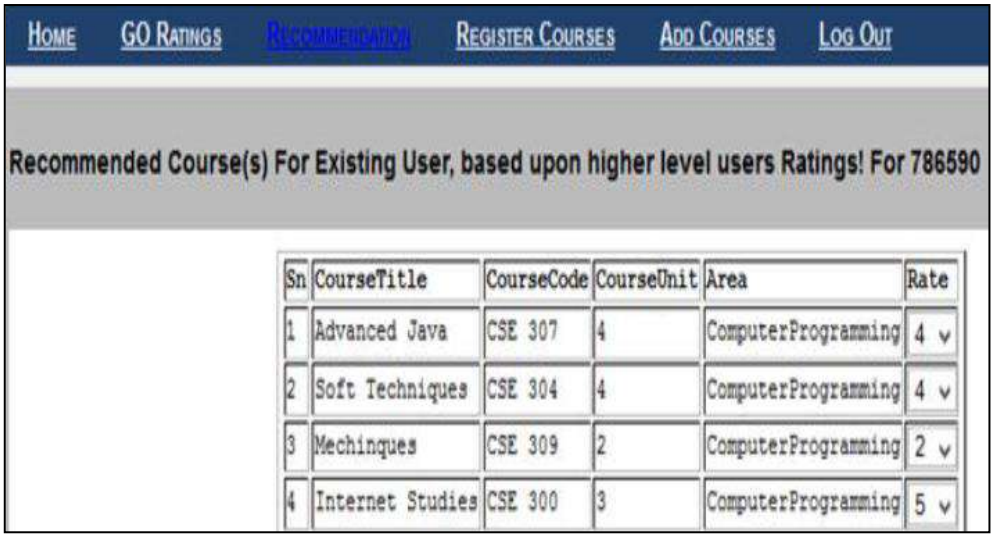

Fig 8: Recommendation Page B

Figure 8 shows recommendation to existing Learner basedupon higher level Learners in same area of specialization.

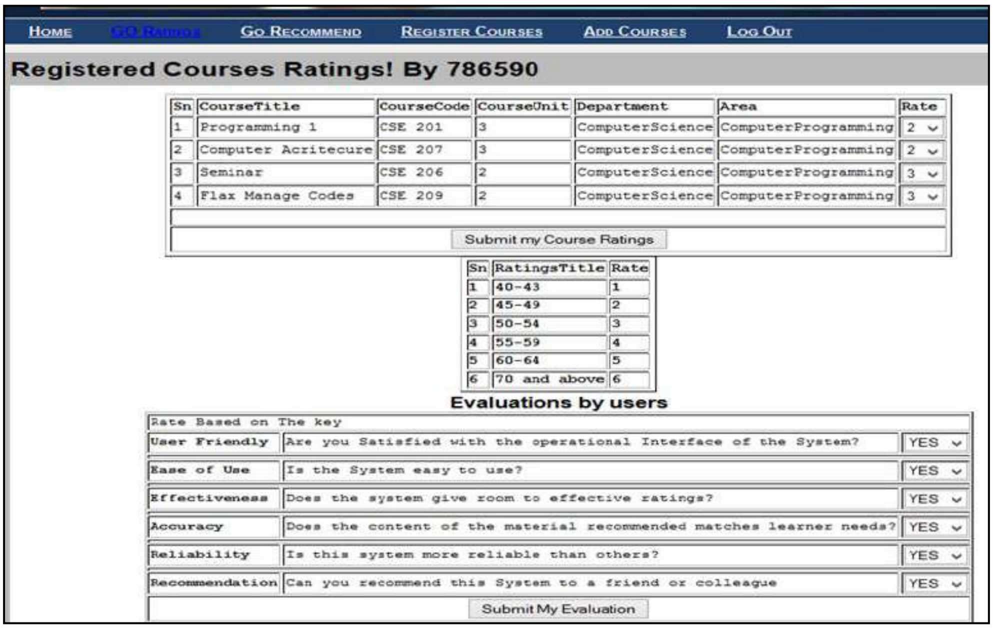

Fig 9: System Evaluation

Figure 9 shows the previous recommendation to the existing user and it is also used to obtain their ratings after undertaking the course.

They can also give and update their feedback on the user friendliness, ease of use, reliability, effectiveness, accuracy, useful recommendation of the System. The existing user provide its ratings for each course and click the submit button. It shows the confirmation that the rating entry is successful.

Result Evaluation

Table 1: Results from student's evaluation of the collaborative filtering technique

Description	YES (%)	NO (%)
User Friendly	90	10
Ease of Use	100	0
Effectiveness	98	2
Accuracy	88	12
Reliability	90	10
Recommendation	95	5

The table above shows the number of students that evaluated the system under the description. Result of figure 9 was shown in the table for one hundred students. Existing students evaluate the courses and submit successfully. The table summarizes their evaluations.

The table above shows the number of students that evaluated the system under the description.

In order to compare the deviation between predictions and the real user specified values, we use the Mean Absolute Error (MAE) as one of the most widely used technique; we computed the average error between the predictions and the *t* ratings as shown in formula:

$$MAE = \frac{\sum_{u,j}^{t} |\bar{P}_{u,j} - r_{u,j}|}{t}$$

Source: Outmane, B. (2012)

Where t the total number of ratings is over all learners Pu, j is the predicted rating for learner u for the learning Object Өj and $r_{u,j}$ is the learner as rating.

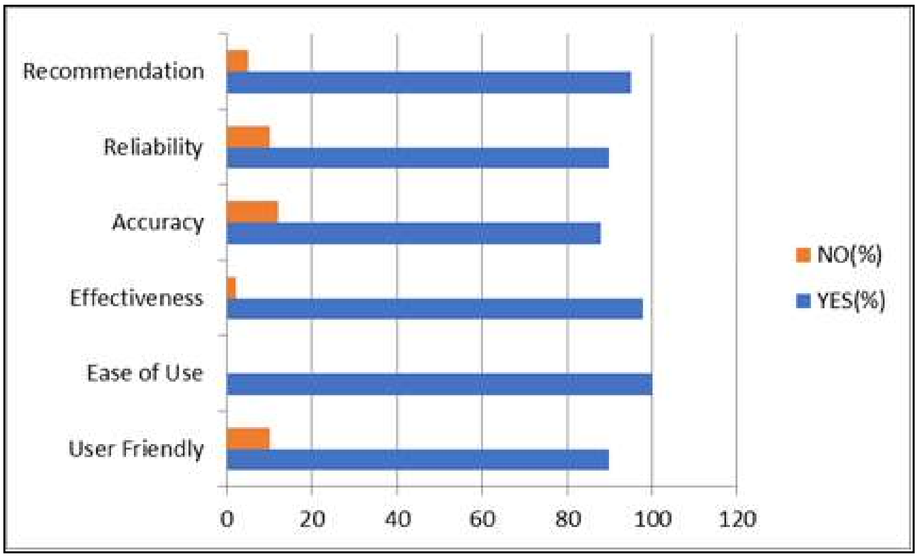

Chart 1: Bar chat illustrating evaluation result

The mean absolute error was derived using the system's predicted ratings for learner u with the real learner u final rating after undertaking the course. We employed mean absolute error (MEA) as metric to show the quality prediction of the recommendation in terms of accuracy.

Table 2: Results from mean absolute error (MAE) to show the quality prediction of the recommendation in terms of accuracy

Neigbourhood size (K)	MAE for collaborative filtering	MAE for hybrid filtering system
5	0.6	0.4
10	0.3	0.1
15	0.13	0.07
20	0.4	0.2
25	0.8	0.3
30	0.5	0.15

In order to measure the efficiency of our algorithm, we employ MAE (mean absolute error) as metric defined above. The smaller MAE value is the more accuracy the prediction is. We can conclude that since the MAE value for Hybrid filtering is lower than the MAE of Collaborative filtering, we say assembling collaborative filtering and stereotype filtering technique tackle the user cold-start problem.

Conclusion and Recommendation

The strategy for ensembling both recommendation technique is switching techniques that select to consider one of the recommender based on a particular situation. The result showed that the satisfaction level of learners are based on learner academic Information. In stereotype, recommendations are issued for new learner by first identifying the category user belongs to by locating preferences of other user in the same category. It is important to know that if demographic information required from the leaner are those that could be considered invasive (privacy intrusion). Learners are not likely to provide them due to fear of their information being compromise. Hence, there is need for developing additional facilities to preserve privacy information and at the same time be able to use them for accurate recommendation.

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