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A Hybrid Personalized Tag Recommendationsfor Social E-Learning System

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ABSTRACT

Collaborative filtering (CF) is one of the most popular techniques behind the success of recommendation system. It predicts the interest of users by collecting information from past users who have the same opinions. Starting recommendation methods like content based recommendation lost its import and the pattern setting collaborative filtering methodology picks up its proficiency in all fields.With a specific end goal to perform a better data recommendation cluster based collaborative filtering methodologies are used these days. Clustering leads to the reduction of huge data set into smaller data set in which all the services are similar to one another. In this paper, a hybrid personalized recommender system based on a clustering algorithm and Collaborative Filtering approach is proposed for social E-Learning systems and the technique is implemented and tested using an E-Learning environmental dataset. At long last this calculation is contrasted and slope one calculation and the execution is dissected by utilizing the measurements Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Keywords: Clustering, Recommendation, Mean Absolute Error, Root Mean Square Error, Social E-Learning Systems.

I. INTRODUCTION

E-Learning is a rapidly growing and important application in the internet and is widely used in many educational communities [1]. Social E-Learning changes the conventional inspiring way of teaching that centers on the teachers and emphasizes students' active learning, thus people pay more and more attention to it. As web technology is to be mature and widely applied, learning resources can be realized in a wide range of publishing and sharing through the internet [2]. Social E-Learning Systems adopted a tagging system in E-Learning environments based on Web 2.0 technology. The Social E-Learning environment creates a highly interactive user friendly system for E-Learning system.

Research on E-Learning has reached more and more attention because of the recent explosive use of the internet. Social E-Learning Systems are a web-based adaptive E-Learning systems which have been focusing on the interrelations between users and the tags. In this environment, the tagging can be acknowledged as the common procedure of joining an applicable student characterized magic word to a record, picture or picture, which helps students to better structure and share in their accumulations of fascinating material. In the Social E-Learning system, the tagging can be regarded as the act of linking of entities such as users, resources and tags [3]. It helps user better way to understand and disseminate their collections of attractive targets. At the point when a student utilizes a tag to an asset in the framework, a multilateral relationship between the students, the asset and the tag are shaped.

Data clustering is a common technique for statistical data analysis. Clustering provides partitioning of a data set into subsets of similar objects or data clusters. Before actually using a clustering technique, the

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first task one has to do is to transform the problem at hand into a numeric representation that can be used by clustering [4]. Clustering segments a dataset into a few gatherings such that the similitude inside a gathering is bigger than that among gatherings [5]. Tag clustering is the procedure of collection of comparative labels into the same cluster and is critical to the accomplishment of social tagging systems. The goal of clustering tags is to detect frequently used tags for the different users. On the tag clustering, similar tags are clustered based on tag weights associated with users [6].

A recommendation system is one of the information filtering systems which predict or retain the particular information that user give to the item. The rating of the item is used to recommend the particular item to another user. So, that the items are rated in two different ways, namely Collaborative Filtering (CF) and content based filtering. In the collaborative filtering, the items are rated based on the users' past experience and the final rating is dependent on the user decision. The content based filtering uses the characteristics of an item with the similar properties. Another approach called hybrid filtering is introduced. This is the combination of content based filtering and collaborative filtering.

In this paper, a hybrid personalized recommender system is proposed for social E-Learning systems. The proposed system combines the Tolerance Rough set-based Particle Swarm Optimization (TRS-PSO-K-Means) clustering algorithm and collaborative filtering techniques and these systemsare implemented and tested against an E-Learning environment dataset. The performance of these techniques is compared based on 'Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).' The evaluation metrics of these techniques is compared based on Precision and Recall.

The proposed work consists of four major tasks:

- Data Extraction: Fetching data from the E-Learning environment (http://www.pumrpelearning.com)
- Data Formatting: Data formatting consists of mapping the tags and users based on tag weights Represented in matrix format
- Tag Clustering: to cluster relevant tags based on tag weights associated with users.
- Recommendation: to Recommend Tags to the Users.

The rest of this paper is organized as follows: Section 2 presents some of the related work. Section 3 Presents Methodology of this research work. In Section 4, the experimental results have been reported. And the conclusion has been addressed in Section 5.

II. RELATED WORK

This section gives a brief review about the clustering and Collaborative Filtering Techniques. The objective of our research work is to create and assess another direction, i.e Personalized Tag Recommendation using Clustering, for future web data mining. Clustering is viewed as an intriguing methodology for discovering likenesses in information and putting comparable information into gatherings [7]. Tag clustering helps us to dissect information as well as enhancing internet searching encounters [8]. Dattolo *et al.* had presented an approach for detecting groups of similar tags and relationships among them. The authors apply clustering processes to find different categories of related tags, presenting three ways of calculating tag weights within a graph: intersection, Jaccard and a more complex approach that considers additional distributional measures of tags in a vector space representation [9]. In Xu *et al.* (2011), the authors have demonstrated a running model of tag clustering based on similarity and he proposed a clustering technique called Kernel information propagation for tag clustering [10]. Begelman *et al.* (2006) presented several clustering techniques and provided some results on del.icio.us and Raw-Sugar to prove that clustering can improve the tagging experience [8]. Shepitsen *et al.* (2008) applied hierarchical clustering algorithm for tag clustering [11]. Sbodio and Simpson (2009) have used self-organizing maps (SOM) to cluster tagged bookmarks.

Collaborative Filtering with clustering technique have been extensively studied by some researchers. Mai *et al.* (2009) designed a neural network based clustering collaborative filtering algorithm in the commerce recommendation system. With the data from web visiting message, the cluster analysis gathers users with similar characteristics. However, it is hard to say that a user's preference for web visiting is relevant to preference in purchasing. Pham *et al.* (2011) proposed a concept to use network clustering technique for social network of users to identify their neighbourhood, and then use the traditional CF algorithms to generate the recommendations.

This work depends on social relationships between users. Simon *et al.* (2013) used a high dimensional parameter-free, divisive hierarchical clustering algorithm that requires only implicit feedback on past user purchases to discover the relationships within the users. Based on the clustering results, products of high interest were recommended to the users. However, implicit feedback does not always provide sure information about the user's preference. In [3], an improved slope one algorithm based on time weight is proposed. It is a collaborative filtering technique. This algorithm overcomes the problem of ratings produced at different times which are weighted equally. Here, different weights are assigned to items at different times [20]. Furthermore this algorithm is compared with original slope one algorithm and the results are evaluated. The results show that the improved slope one algorithm improves precision. Sparsity of the source data set is the major reason causing the poor quality. To solve the problems of scalability and scarcity in the collaborative filtering, [4] proposed a personalized recommendation approach joins the user clustering technology and item clustering technology. Users are clustered based on users' ratings on items, and each user cluster has a cluster center. Based on the similarity between target user and cluster centers, the nearest neighbors of target user can be found and smooth the prediction where necessary.

III. PROPOSED METHODOLOGY

The Proposed Methodology for Tag Recommendation comprises the following steps:

(a) Data extraction

(b) Data formatting

(c) Clustering

(d) Recommendation

3.1. Data Extraction

The experimental dataset can be extracted from the E-Learning environment (http://www/pumrpeleaning.com), which helps users to search relevant resources using tags. Table 1 shows the example dataset extracted from the social E-Learning environment. In clustering tag data, the users were treated as attributes and the tags are treated as objects.

Table 1
Social E-Learning dataset

User ID	*Tag name*	*Tag count*
1	Android	7
2	Java	2
1	Networking	8
1	Distributed system	9
2	Operating system	4
3	Grid computing	9
2	Cloud computing	5
4	java	7

3.2. Data Formatting

After fetching the dataset from the E-Learning environment, the next step is to format the data set. i.e converting the dataset into matrix representation. Table 2 shows the matrix representation of the tag dataset. Rows corresponds to tags and columns corresponds to the users.

In the tag matrix,

- n represents tags, M represents users, W_{ij} represents tag weight associated with users.

Table 2
Dataset format

	User 1	*User 2*	*User 3*	*User 4*	*User 5*
Android	7	9	18	6	5
java	10	14	11	2	2
Networking	0	6	9	41	9
Distributed system	0	14	23	30	7
Operating system	0	1	19	4	8
Grid computing	5	0	25	3	2

3.3. Clustering

Even after the above Data Formatting procedure, the tag data is still not ready for effective application in a personalization recommendation system based on collaborative filtering, because the number of user tag data is very large. The number of inputs of the personalization recommendation system will need to be equivalent to the number of transactions, and because this number is so large, it will not be feasible with this data [19]. Clustering tag data is the process of grouping the similar tags into the same cluster-based on tag weight by applying clustering techniques. Tags in the same cluster have been often used tags by users. The TRS-PSO-K-Means clustering algorithm is used for Tag Clustering. The clusters are formed based on the tag weight.

Table 3
Experimental dataset

	U1	*U2*	*U3*	*U4*
Tag 1	7	0	0	5
Tag 2	9	6	1	0
Tag 3	18	9	19	25
Tag 4	6	41	4	3
Tag 5	5	9	8	2
Tag 6	7	0	0	5
Tag 7	9	6	1	0
Tag 8	18	9	19	25
Tag 9	6	41	4	3
Tag 10	5	9	8	2

The above table shows the sample dataset and consist of 10 tags and 4 users. After clustering, tag 1, tag 2, tag 5, tag 6, tag 7 and tag 10 are the members of the cluster 1 whereas tag3, tag4, tag8, tag9 are the members of the cluster 2. Tolerance Rough Set Model (TRSM) was developed by Ho, T.B, and Nguyen N.B as basis to model tags and Users in information retrieval, Social Tagging Systems, etc. [16]. With its power to deal with vagueness and fuzziness, TRSM seems to be a promising tool to model relations between tags and Users [15].

Algorithm 1: **TRS Approach (Intelligent approach) (For Finding K)**
Input: *Set of N Tagged Resources, threshold* $\boldsymbol{\delta}$.   ***Output****: Number of K- clusters*   ***Step 1****: Construct similarity matrix between Tagged Bookmarks using eq.3.1* $$Cosine\ similarity = \frac{\sum_{i=1}^{t} x_i y_i}{\sqrt{\sum_{i=1}^{t} {x_i}^2 + \sum_{i=1}^{t} {y_i}^2}} \quad (3.1)$$ ***Step 2****: Find similarity upper approximation using eq.3.2 for each Tagged Bookmark based on threshold* $\boldsymbol{\delta}$. $$\bar{R}X = \{x \in U : R(x) \cap X \neq 0\} \quad (3.2)$$ ***Step 3****: Find centroid for each set of tags' upper approximation*   ***Step 4****:Merge similar centroids into one cluster (set) and set the value of K as distinct number of sets*   ***Step 5:*** *Initialize the number of clusters to K and centroids as cluster representatives.*

PSO is computationally efficient and easier to implement when compared with other mathematical algorithms and evolutionary algorithms. In PSO, N particles are moving around in the D dimensional search spaces. Each particle moves towards the nearest region [14]. Each particle communicates with some other particle and is exaggerated by the best centroid point found by any member of its current centroid value p_i. The vector p_i for that best neighbour and is denoted by p_g. Initialize the particle's location best known position to its initial position: $p_i \leftarrow x_i$. Then correspondingly update the particles or the position of the centroid value position and their velocity (eq. 3.3) to recognize the best planetary position (eq. 3.4) or of the best centroid value to group the information. These steps are iterated until a termination criterion is satisfied. Ultimately, after finding the global best position, best value of cluster centroid is obtained.

$$v_{id} = w * v_{id} + C_1 * rand1 * (P_{id} - x_{id}) + C_2 * rand2 * \left(P_{gd} - x_{id}\right) \quad (3.3)$$

$$x_{id} = x_{id} + v_{id} \quad (3.4)$$

Where, V_{id} : velocity of particle, x_{id} : current position of particle

W : weighting function,

$$\mathrm{w} = \mathrm{w}_{\max} - \frac{\mathrm{w}_{\max} - \mathrm{w}_{\min}}{\mathrm{iter}_{\max}} * \mathrm{iter} \quad (3.5)$$

w_{min}, w_{max} : initial and final weight

iter: current iteration, itermax : maximum iteration

c_1&c_2: determine the relative influence of the social and cognitive components

p_{id}: pbest of particle i, p_{gd} : g_{best} of the group.

The personal best position of particle is calculated as follows

$$\mathrm{p_{id}}(\mathrm{t}+1) = \begin{cases} \mathrm{p_{id}}(\mathrm{t}) & \text{if } \mathrm{f}(\mathrm{X_{id}}(\mathrm{t}+1)) \geq \mathrm{f}(\mathrm{p_{id}}(\mathrm{t})) \\ \mathrm{X_{id}}(\mathrm{t}) & \text{if } \mathrm{f}(\mathrm{X_{id}}(\mathrm{t}+1)) < f(\mathrm{p_{id}}(\mathrm{t})) \end{cases} \quad (3.6)$$

The particle to be drawn toward the best particle in the swarm is the global best position of each particle. At the start, an initial position of the particle is considered as the personal best and the global best can be identified with minimum fitness function value [17].

Algorithm 2: TRS-PSO-K-Means Clustering Algorithm
Input: D *set of N Tags,* ***K*** *-number of clusters,* ***δ*** *– upper approximation threshold.* ***Output:*** ***K*** *overlapping clusters of tags from* ***D*** *with associated membership value* ***Step 1:*** *Initialize Number of clusters and its centroids using TRS approach (defined in Algorithm 1)* ***Step 2:*** *Assign each vector in the data set to the closest centroid vector* ***Step 3:*** *Calculate the fitness value for each Tag vector and update the velocity and Particle position, using equations (3.3) and (3.4) and generate the next solutions* ***Step 4:*** *Repeat steps (2) and (3) until one of the following termination conditions is Satisfied.* *(a) The maximum number of iterations is exceeded* *or* (b) *The average change in centroid vectors between iterations is less than a predefined value.*

3.4. Recommendation

A hybrid methodology develops as an issue decision in research philosophy. It joins components of both subjectivity and objectivity methodological methodologies, as per the objectives, content, and connection of the examination and inclination of the scientist himself/herself. Since it is conceivable to consolidate the two important methodological methodologies in different courses, there are a few conceivable cross breed systems in research. Recommendation is the sub class of information filtering system. It is the process of predicting the rating or preference of the user given for an item [18]. This recommendation system enhances the user experience by assisting user in finding information and reduces search and navigation time.

In this section, A Hybrid Personalized Recommender System For Social E-Learning Systems is proposed. The working process of this algorithm comprises the following steps

1. Cluster Selection
2. Similarity Computation
3. Neighborhood selection
4. Prediction

Cluster selection: Among the Number of clusters formed by using TRS-PSO-K means, a single cluster is selected.

Similarity computation: Item similarity computation is the technique for computing similarity between the tags. This can be done by identifying the users those who are given weights for similar tags. Based on this, the similarity computation techniques are applied to determine the similarity between the tags. Let i and j be the tags. Then the similarity between the tags are represented as $sim_{i,j}$. In this work, correlation based similarity computation technique is adapted. In this case the similarity is computed based on the correlation among the users. Pearson correlation coefficient is the preferred choice.

Let u_i are the users who are given weights both the tags a and b. then the similarity between the tags is computed as follows.

$$sim\ (a,b) = \frac{\sum_{u \in U_a \cap U_b} \left(r_{u_i,a} - \overline{r_a}\right)\left(r_{u_i,b} - \overline{r_b}\right)}{\sqrt{\sum_{u \in U_a \cap U_b} \left(r_{u_i,a} - \overline{r_a}\right)^2} \sqrt{\sum_{u \in U_a \cap U_b} \left(r_{u_i,b} - \overline{r_b}\right)^2}} \tag{3.6}$$

Here u_a is a set of users who rated a while u_b is a set of users who rated b, u is a user who both rated a and b, $r_{u,a}$ is the rating of a given by u, $r_{u,b}$ is the rating of b given by u and r_a is the average rating of a , and r_b is the average rating of b. The value of sim(a, b) is in the interval of [-1,1].

Neighborhood selection: The next step in recommendation algorithm is neighborhood selection. The neighbors for the recovery tag is selected. This is done by comparing the similarity value with the threshold value. If the similarity value exceeds threshold value, then that tag is considered as neighbor for the recovery tag. The neighbors of the target tag are determined according to the following formula

$$Neighbor(a) = \{b \mid R_{sim}(a,b) > \gamma, a \neq b\} \tag{3.7}$$

Here $R_{sim\,(a,b)}$ is the rating similarity between tag a and tag b. ³ is the rating similarity threshold

Prediction computation: Based on the predicted rate, the tags are recommended to the users. Let u be the active user and a be the recovery tag, then the predicting rate p $_{(u,a)}$ is computed as follows

$$P_{u,a} = \overline{r_a} + \frac{\sum_{b \in N(a)} (r_{u,b} - \overline{r_b}) * R_{sim}(a,b)}{\sum_{b \in N(a)} R_{sim}(a,b)} \tag{3.8}$$

$\overline{r_a}$ is the average rate given to tag a.$b \in N(a)$ is the neighbor set of tag a. $r_{u,b}$ is the rate given by the user u to tag b. $R_{sim}(a, b)$ is the rating similarity between tag a and tag b.

Algorithm 3: Proposed Work **Recommendation Techniques**

Input: Clustered tags and their ratings
Output: recommended tags for the users
Step 1: Choose the Cluster
Step 2: Compute Rating Similarity between tags R_{sim}
Step 3: Select Neighbor
    If $R_{sim\,(a,b)} > \gamma$ *, Then b is the neighbor of a*
Step 4: Prediction Computation $P_{(u,a)}$
    If $P_{(u,a)}$*> threshold value*
    Then a is recommendable tag to the user u
Step 5: repeat step 2 to 4 to predict the values for all other tags in the cluster..

We provide an example to illustrate this recommendation algorithm.

Step 1: Consider cluster 1 which is having the members Tag 1, Tag 2, Tag 5, Tag 6, Tag 7, and Tag 10.

Table 4
Resultant Cluster 1

	Cluster 1			
	U1	*U2*	*U3*	*U4*
Tag 1	7	0	0	5
Tag 2	9	6	1	0
Tag 5	5	9	8	2
Tag 6	7	0	0	5
Tag 7	9	6	1	0
Tag 10	5	9	8	2

Table 5
Rating Similarity between Tags

	Recovery tag pairs	*Rating similarity*
Rating similarity with respect Tag 6	(Tag 6, Tag 1)	1
	(Tag 6, Tag 2)	0.3311
	(Tag 6, Tag 5)	-0.7997
	(Tag 6, Tag 7)	0.3311
	(Tag 6, Tag 10)	-0.7997

Step 2: Using eq.3.6, the rating similarity is computed between the tags of cluster 1 by using the following Pearson correlation coefficient which ranges in value from -1 to +1. The rating similarities between Tag 6 and every other tags in cluster 1 are calculated and shown the following table.

Step 3: The neighborhood Selection for the target recovery tag is calculated using the equation (3.7) here, the rating similarity threshold value is set as $\gamma = 0.5$.

The rating similarity between (Tag 6, Tag 5) and (Tag 6, Tag 10) exhibits negative correlation, hence it is omitted. The rating similarity between (Tag 6, Tag 2) and (Tag 6, Tag 7) is positive. But it does not exceed the threshold value. Hence it is also omitted. But (Tag 6, Tag 1) pair is positive and it is greater than the threshold value, hence Tag 1 is chosen as the neighbour of Tag 6. i.e.

Neighbour (Tag 6) = Tag 1

Step 4: Using Eq.3.8 to find the predicted rate and the tags are recommended to the users.Those results are shown in Table 2. Using that data, the proposed recommendation algorithm is applied as mentioned in section III from step 1 to step 5. The resulting table shows the recommendable tags for the users in the system. It is shown in the following table 4.1.

Table 6
Recommended Tags

Users	*Recommended tags*
User 1	Tag 1,Tag 2, Tag 5,Tag 6, Tag 7,Tag 10
User 2	Tag 1,Tag 2,Tag 5,Tag 7,Tag 10
User 3	Tag 5,Tag 10
User 4	Tag 1,Tag 6

Repeat the steps from 2 to 4 to calculate the predicted value for all other tags in cluster and should be recommended to the users

IV. EXPERIMENTAL ANALYSIS AND RESULTS

Social E-Learning (http://www.pumrpelearning.com/) data set is collected fromPumrpelearning.com. pumrpelearning founded in 2013 is a Social E-learning website where users can SearchLearning Resources and the system automatically assignsweights to the particular tags. Other data sets are also used for comparison, because they are the mostly used data sets by researchers and developers in the collaborative filtering domain.The information about the data sets contain names of dataset, the number of tags and number of users/bookmarks/Resources, which are given in Table 7. In clustering tag data, the Users/ Bookmarks/Resources were treated as attributes and the tags are treated as objects.

Table 7
Dataset Description

S. No.	*Dataset*	*Tags*	*Users/Bookmarks*	*URL*
1	pumrpelearninggg	42	252	*http://www.pumrpelearning.com*
2	Social	53388	12616	*http://nlp.uned.es/socialtagging/socialodp2k9/*
3	tags2con	2832	1474	*disi.unitn.it/~knowdive/dataset/delicious/*

4.1. Performance Metrics

The proposed hybrid item-based collaborative filtering algorithm is compared with the improved slope one algorithm. The metrics used for comparison are MAE (Mean Absolute Error) and RMSE (Root Mean Square Error).

Mean Absolute Error

The MAE is the average over the verification sample of the absolute values of the differences between forecast and the corresponding observations. It measures accuracy for continuous variables.

MAE is represented as

$$MAE = \frac{1}{n}\sum_{i-1}^{n} |p_i - q_i| \tag{3.9}$$

Where p_i is the predicted value and q_i is the true value.

Root Mean Square Error

RMSE is the difference between forecast and corresponding observed values are each squared and then averaged over the sample. RMSE can be calculated as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{3.10}$$

Where n is the total number of users. y_i is the predicted rate and y_i is the actual rate.

The following table shows the comparison between hybrid item-based collaborative filtering algorithm and the improved slope one algorithm based on the MAE and RMSE metrics.

Table 8
Performance Metrics

	Pumrpelearning		*Social*		*Tags2con*	
	MAE	*RMSE*	*MAE*	*RMSE*	*MAE*	*RMSE*
Proposed Algorithm	1.2	2.1216	1.8	2.59	1.54	2.37
Improved slope one algorithm	1.563	3.2140	2.6	3.65	1.91	3.08

Table 8 shows that the proposed hybrid item based collaborative filtering algorithm has minimum Mean Absolute Error and Root Mean Square Error when compared with the improved one slope algorithm.

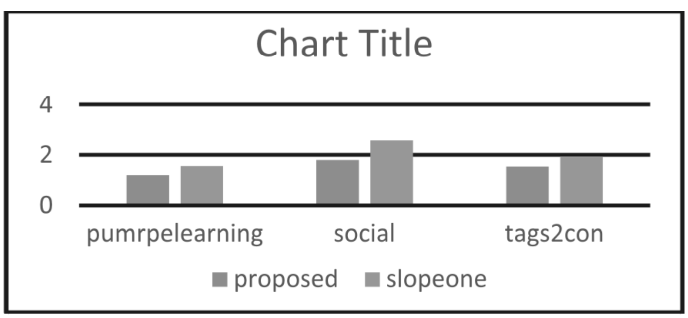

Figure 4.1: Mean Absolute Error

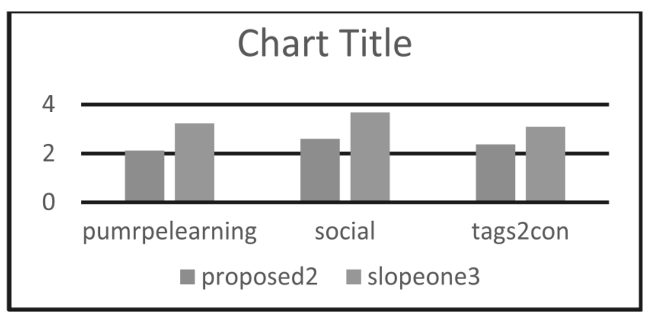

Figure 4.2: Root Mean Square Error

4.2. Evaluation Metrics

To evaluate our offered framework; we applied recall and precision metric which were defined in information retrieval. These metrics are defined in tags as follows:

Precision

It is defined as the ratio of the number of recommended objects collected by users appearing in the test set to the total number of recommended objects. This measure is used to evaluate the validity of a given recommendation list. The precision can be formulated as, in which represents the number of recommended products collected by users appearing in test set, and is the total number of recommended products.

$$Precision = \frac{|user\ tags\ \cap recommended\ tags\ |}{|recommended\ tags|}$$

Recall

It is defined as the ratio of the number of recommended objects collected by users appearing in the test set to the total number of the objects actually collected by these users. The larger recall corresponds to the better performance. The Recall can be formulated as, in which represents the number of recommended products collected by users appearing in test set, and is the total number of these users' actual buying.

$$recall = \frac{|user\ tags\ \cap recommended\ tags\ |}{|favourite\ tags|}$$

Table 9
Evaluation Metrics

	Pumrpelearning		*Social*		*Tags2con*	
	Precision	*Recall*	*Precision*	*Recall*	*Precision*	*Recall*
Proposed Algorithm	0.771	0.329	0.658	0.279	0.886	0.426
Improved slope one algorithm	0.621	0.439	0.559	0.394	0.742	0.349

Table 9 shows that the proposed hybrid item based collaborative filtering algorithm has better results when compared with the improved one slope algorithm based on the evaluation metrics like precision and recall.

V. INTERPRETATION OF RESULTS

The tag data was gathered from the social E-Learning framework developed in the department of computer science Periyar University. The framework has two modules admin and user. The admin module is used for adding the resources and user module is used for accessing that resource. The user first registers in the social E-Learning web site and the user can search the resources using small keywords called tags.

Figure 5.1: E-Learning Framework

In this paper, Hybrid Personalized Recommender System is proposed for Social E-Learning System. In the process of clustering, TRS-PSO-K-Means algorithm is applied to overcome the local optimal problem caused by K-means. Finally, we generate recommendation results for the corresponding target users. Detailed numerical analysis on a Social E-Learning dataset indicates that our new collaborative filtering approach based on users-tag clustering algorithm outperforms many other recommendation methods.

This study is a first endeavor from the alternate point of view of personalization and to best of our insight. This endeavor is another course in the field of Social E-Learning environment. The results got are exceptionally empowering, demonstrating the viable appropriateness of E-Learning framework, both from the perspective of the understudies and the educators. This framework received Web2.0 features like tagging and bookmarking. Clustered tag data is used for predicting the user preferences. After clustering the resources based on the tags is provided by the userand it can be clustered like the resources that are mostly related to user preferences.

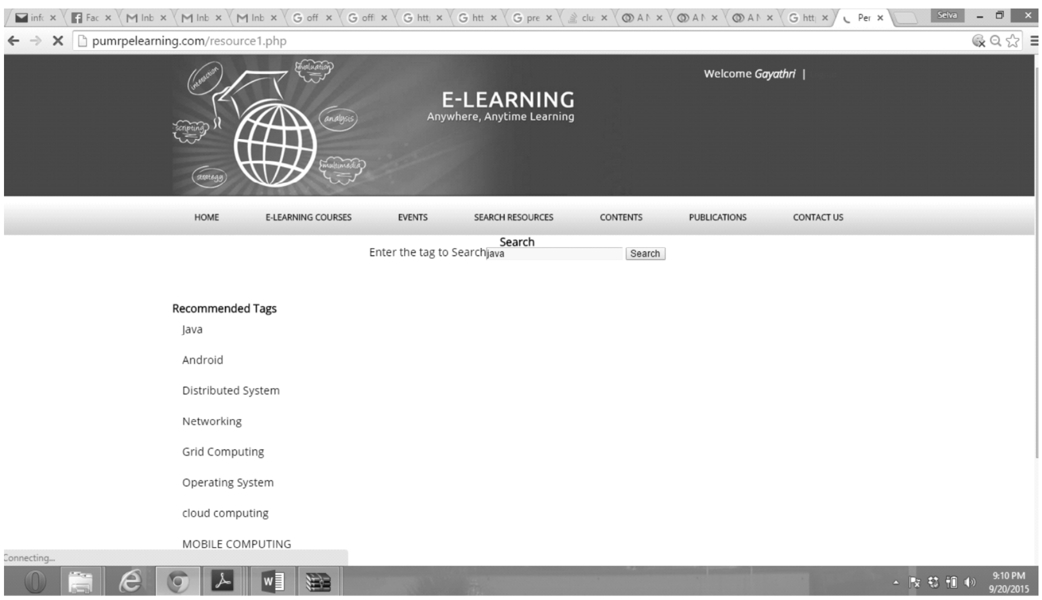

Figure 5.2: Recommended Resources

Figure 5.3: Web2.0 Enabled E-Learning (Pumrpelerning.com)

The Collaborative Filtering has turned into the most broadly utilized strategy to prescribe tags for users. The Collaborative Filtering incorporates memory-based technique and model-based scheme. The memory-based system first computes the similitude among users and after that chooses the most comparable users as the neighbors. Recommendation model helps users to find out their potential future likes and interests. It recommends good products to users and satisfies the users' demands as far as possible. The application of clustering techniques reduces the sparsity and improves the scalability of the recommendation model since the similarity can be calculated only for users in the same clusters. An excellent recommendation method meets high accuracy and certain diversity and can enhance the quality of personalized service.

VI. CONCLUSION AND FUTURE WORK

Recommendation systems are introduced to provide tag recommendations for the users based on computing the similarities between the users. In this paper, a hybrid TRS-PSO-K-Means clustering and tag-based collaborative filtering algorithm is proposed. This algorithm works based on the weights given by the users for the tag items. Furthermore, this algorithm is compared with another existing slope one algorithm. Results shows that the proposed algorithm performs better than the slope one algorithm.

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