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A Comprehensive Survey of Neighborhood-Based Recommendation Methods used in E-Learning Recommender Systems

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Abstract – This paper presents the essentials of the background, available literature and technologies presently available in e-leaning specifically recommender systems and its range of applications, different techniques used for the general recommender systems, e-learning recommender systems and the specific neighborhood-based recommender methods used. A comprehensive survey has been carried out to elucidate the types of neighborhood-based recommendation methods used in e-learning recommender systems. The paper highlights these methods with an comparative analysis of the recommendation methods.

Keywords – E-learning, personalized learning, learning styles, recommender systems, neighborhood-based methods

I. INTRODUCTION

One of the best ways to deal with the problems in e-learning is personalization, by supporting learners independently based on their characteristics. *Personalization* in e-learning systems takes place when the systems uniquely address a learner's needs and characteristics. This will help in improving the learner's satisfaction and overall quality of learning and outcome. To support personalization, *recommender systems* can be employed. They facilitate personalization by recommending suitable learning objects to learners based on their individual needs and characteristics.

1.1 RECOMMENDER SYSTEMS

Recommender systems were developed as per the need of the times. In the field of *e-commerce* and *entertainment* naïve customers were in need of help in the form of guidance and suggestions from knowledgeable customers. These guidance and suggestions were termed as *recommendations*. The recommendations were for *items* that *similar users* (those with similar tastes) had liked. The *rationale* is that if the active user agreed in the past with some users, then the other recommendations coming from these similar users should be relevant as well and of interest to the active user.

As e-commerce domain began to develop, a pressing need emerged for providing recommendations derived from filtering the whole range of available alternatives. Since the products and services exploded into the market and there were too many of them, the buyers needed better, smarter and quicker *suggestions/recommendations.* The explosive growth and variety of information available on the web and the rapid introduction of new e-business services (buying products, product comparison, auction, etc.) frequently overwhelmed users, leading them to make poor decisions. The availability of choices, instead of helping the customers, were instead confusing and demoralizing them. In fact, multiple choice, with the hidden implications of freedom, autonomy, and self-determination can become excessive [1]. Recommender systems have proved in recent years to be a valuable means for coping with the information overload problem. Ultimately a recommender system addresses this phenomenon by pointing a user towards new, not-yet-experienced items that may be relevant to the user's current task.

1.1.1 The Spectrum of Recommendation Applications

A short review of the products proposed and the objectives achieved by different recommender systems are shown in *Table 1.1.* Huge number of these recommender systems are centered around customary web based business applications for different items, including books, movies, recordings, travel, and different merchandise and enterprises.

Table 1.1 Different Recommender Systems

Recommender System	Products and Services
www.Amazon.com	Multiple items
www.Netflix.com	Cinema
www.Jester.com	Humour
www.GroupLens.org	News and Info

www.MovieLens.com	Cinema
www.Last.fm	Songs and Music
www.News.google.com	News and Info
www.Google.com	All info
www.Facebook.com	Social Networking
www.Pandora.com	Songs and Music
www.YouTube.com	Online video
www.Tripadvisor.com	Trip Details
www.IMDb.com	Cinema

1.1.2 Recommendation Methods

To understand and analyze the application developments of recommender systems, this section first reviews the main recommendation methods.

Content-based recommendation Methods

Content-based (CB) recommendation methods recommend books, writings or items that are similar to items previously preferred by a specific user [2]. The underlying principles of CB recommender systems are: 1) the description of an item is liked by an user is identified based on the attributes or preferences and they are maintained in a user profile, 2) the user profile is compared with the item's attribute, and based on the similarity, it will be recommended.

In CB recommender systems, two techniques are used to provide recommendations. One technique makes use of heuristic traditional data mining method, namely, cosine similarity measure. The other technique provides recommendations using statistical learning and machine learning methods.

Collaborative filtering-based recommendation methods

Collaborative filtering (CF) based recommendation methods make recommendations based on the opinions of other people who share similar interests [3]. The CF technique can be divided into user-based and item-based CF approaches. In the user-based CF approach, a user will receive recommendations of items liked by similar users. In the item-based CF approach, a user will receive recommendations of items that are similar to those they have loved in the past.

There are many methods, such as by*Pearson correlation-based similarity, constrained Pearson correlation (CPC)-based similarity, cosine-based similarity,* or *adjusted cosine-based measures,* used to calculate the similarity between users or items can be calculated When calculating the similarity between items using the above methods, only users who have rated both items are considered. This can affect the similarity accuracy when items which have received a very small number of ratings express a high level of similarity with other items. To improve similarity accuracy, an enhanced item-based CF approach was presented by combining the adjusted cosine approach with *Jaccard metric* as a *weighting scheme*. To calculate the similarity between users, the *Jaccard metric* was used as a weighting scheme with the CPC to obtain a weighted CPC measure. To solve the disadvantage of the single-rating based approach, multi-criteria collaborative filtering was developed [4].

Knowledge-based recommendation methods

Knowledge-based (KB) recommendation methods offer items to users based on knowledge about the users, items and/or their relationship. Usually, KB recommendations maintain knowledge repository of how a particular item meets a specific user's need [5]. Case-based reasoning is a common expression of KB recommendation method in which case-based recommender systems represent items as cases and generate the recommendations by retrieving the most similar cases to the user's question or the profile. *Ontology*, as a formal knowledge representation method, represents the domain concepts and the relationships between those concepts. It has been used to express domain knowledge in recommender systems [6]. The semantic similarity between items can be computed based on the domain ontology.

Hybrid recommendation methods

A *hybrid* recommendation method is one that combines the best features of two or more recommendation techniques into one method [7]. Hybrid methods help to achieve better performance and overcome the drawbacks of traditional recommendation techniques. *Burke* classifies seven basic hybrid models: weighted, mixed, switching, feature combination, feature augmentation, cascade and meta-level. The most usual method in the existing hybrid recommendation techniques is to combine the CF recommendation techniques with the other recommendation techniques in an attempt to avoid cold-start, sparseness and/or scalability problems [8].

II. Survey of E-Learning Recommender Systems

In the e-learning area various recommender systems have been acquainted all together which propose learning resources to clients. Such frameworks could possibly assume a critical instructive part, considering the assortment of learning resources that are distributed on the web and the advantages of coordinated effort amongst tutors and learners [9]. The accompanying sections assess some ongoing methodologies and give an appraisal of their status of improvement and assessment.

Altered Vista [10] investigated a few significant issues, for example, the plan of its interface, the improvement of non-legitimate metadata to store client gave assessments, the outline of the framework and the survey plot it utilizes [11], and additionally comes about because of pilot and exact examinations from utilizing the framework to recommend to the individuals from a network both fascinating resources and individuals with comparative tastes and convictions [12].

RACOFI (Rule Applying Collaborative Filtering) Composer System [13] is another leading recommender system. The RACOFI innovation supports the business site *inDiscover (http://www.indiscover.net)* for music tracks recommendation. Also, different analysts have announced embracing RACOFI's approach in their own frameworks too [14].

The *QSIA (Questions Sharing and Interactive Assignments)* for learning resource sharing, surveying and recommendation has been created by *Rafaeli* [15]. This framework is used as a part of the setting of online networks, in order to address the social aspects in learning and to advance collaboration, online recommendation, and further development of learner communities. Rather than building up an ordinary mechanized recommender system, Rafaeli construct QSIA with respect to a generally client controlled recommendation process. The system has been actualized and utilized as a part of the setting of a few learning circumstances, for example, knowledge sharing among workforce and showing collaborators, secondary teachers and among understudies, however no assessment comes about have been accounted for so far [16].

In this pool for collaborative filtering of learning resources, the *CYCLADES* framework [17] has proposed a domain where clients inquiry, get to, and assess digital resources accessible in repositories found through the *Open Archives Initiative (OAI, http://www.openarchives.org).* Similar framework is the *CoFind model* [18]. It additionally utilizes digital resources that are unreservedly accessible on the web however it took after another approach by applying out of the blue *folksonomies* (labels) for recommendations. The CoFind developers expressed that predictions as per preferences were insufficient in a learning setting and along these lines more client driven bottom-up categories like folksonomies are essential.

Gradually neighborhood-based arrangement of collaborative filtering algorithms have been attempted keeping in mind the end goal to help learning object recommendation by *Manouselis et al.* [19]. An intriguing result from this examination in contrast with beginning tests utilizing similar algorithms [20], is that it appears that the performance of similar algorithms is changing, contingent upon the setting where testing happens.

A different approach to learning resources' recommendation has been trailed by *Shen and Shen* [21]. They have developed recommender system for learning objects that depends on sequencing rules that assists users through the concepts of an ontology of topics. A comparative sequencing system has been presented by *Huang et al.* [22]. It utilizes a *Markov chain model* to calculate transition probabilities of conceivable learning objects in a sequenced course of study. The model is upheld by an entropy-based approach for finding at least one recommended learning way. A pilot execution has been sent and tried in a *Taiwanese college*, including around 150 clients.

Tang and McCalla proposed an evolving e-learning system, open into new learning resources that may be found online, which includes a hybrid recommendation service [23]. The creators examined a few methods to improve the execution of their framework, for example, the utilization of fake students. They have additionally listed an assessment investigation of the framework with genuine students [24].

A fairly simple recommender system without considering any preferences or profile information of the learners was developed by *Janssen et al.* [25]. *Nadolski et al.* [26] made a reproduction domain for various mix of recommendation algorithms in hybrid recommender system keeping in mind casual learning systems.

The *ISIS framework* receives a hybrid approach for recommending learning resources was proposed by *Hummel et al.* [27]. The creators expand upon a past simulation system developed by *Koper* [28] keeping in mind the end goal to propose a system that combines social-based (using data from other learners) with information-based (using metadata from learner profiles and learning activities) in a hybrid recommender system. They likewise planned an exploration of different avenues regarding genuine students. *Drachsler et al.* [29] as of late revealed the exploratory outcomes of the ISIS model. They found a positive critical impact on efficiency (time taken to finish the learning objects) of the learners following a runtime of four months. It is a decent case of a system that is following the most recent patterns in learning determinations for speaking to student profiles and learning exercises.

A similar gathering as of late built up a recommender system called *ReMashed* [30] that tends to help learners in casual learning systems. The clients of ReMashed can rate the information of all clients in the framework. The ratings are utilized for collaborative filtering recommendations in view of the *Duine expectation motor* [31]. A comparable approach is trailed by the proposed *Learning Object Recommendation Model (LORM)* that likewise follows a hybrid recommendation algorithmic approach and depicts assets upon different attributes, yet has not yet answered to be executed in a real framework [32].

Another hybrid recommendation approach has been received in the *CourseRank framework (https://courserank.stanford.edu/CourseRank/fundamental)* that is utilized as an informal course used for *Stanford university* students. In this system the recommendation process is seen under the crystal of questioning a social database with course and student data [33]. The framework has been first set in September 2007, drawing in heaps of enthusiasm from its clients: it has been found that over 70% of the Stanford students use it [34].

Other research outcomes are by the virtual university of *Tunis (RPL stage, http://cours.uvt.rnu.tn/rpl/)* [35], *Gomez-Albarran and Jimenez-Diaz* [36], the *APOSDLE EU-project (http://www.aposdle.tugraz.at),* and *the A2M prototype* [37]. Recommendations to cell phones and *PDAs* have also been explored [38]. All the details are summarized in *Table 1.2*.

Table 1.2 E-Learning Recommender Systems

System	Status	Evaluator Focus
Altered Vista	Complete	Method, Model
RACOFI	Sample	Method
QSAI	Complete	—
CYCLADES	Complete	Method
CoFind	Sample	Model
Learning object sequencing	Sample	Model
Evolving e-learning system	Complete	Method, Model
ISIS - Hybrid Personalised Recommender System	Sample	Method, Model
Multi attribute Recommendation Service	Sample	Method
Learning Object Recommendation Model	Progress	—
RecoSearch	Progress	—
Simulation environment	Complete	Method
ReMashed	Complete	Method, Model
CourseRank	Complete	Model
CBR Interface	Sample	—
APOSDLE	Sample	—
A2M	Sample	—
Moodle	Sample	Method, Model
LRLS	Sample	Model
RPL	Sample	Model

III. A Comprehensive Survey of Neighborhood-based Recommendation Methods

The appearance and development of online markets has considerably affected the propensities for shoppers, giving them access to a more prominent assortment of items and data on these merchandise. While this opportunity of procurement has made online trade into a multibillion dollar industry, it additionally made it more troublesome for customers to choose the items that best fit their needs. One of the fundamental arrangements proposed for this data over-burden issue are recommender systems, which give automated and personalized recommendations of products to consumers. Recommender systems have been utilized as a part of a wide assortment of utilizations, for example, the recommendation of books and CDs, music, films, news, jokes and site pages.

The main issue in recommendation is estimating the response of a user new items based on the information available in the system, and based on this suggest new and original items whose response is high. The type of *user-item responses* differs, and falls in any one of three categories: *scalar*, *binary* and *unary*. *Scalar responses*, also known as *ratings*, are numerical (e.g., 1-5 stars) or ordinal values (e.g., strongly agree, agree, neutral,disagree, strongly disagree). *Binary responses* have only two possible values encoding opposite levels of appreciation (e.g., like/dislike or interested/not interested). Finally, *unary responses* note the interaction of a user with an item (e.g., purchase, online access, etc.). User responses can also be got *implicitly* from purchase history or access patterns [39]. For example, the amount of time spent by a user browsing a specific type of item can be used as an indicator of the user's interest for the item type.

1.3.1 Formal Definition of the Problem

Few terms and notations need to be presented. U denotes the group of users in the system, I is the set of items, R the set of ratings stored in the system, and the set of possible values for a rating by S (e.g., $S = [1, 5]$ or $S = \{like, dislike\}$). No more than one rating can be done by any user $u \in U$ for a particular item $i \in I$ and notes as r_{ui}. To identify the subset of users that have rated an item i, the notation U_i is used. I_u represents the subset of items that have been rated by a user u. The items that have been rated by two users u and v, i.e.

$I_u \cap I_v$, and I_{uv} is marks this concept. In a similar way U_{ij} is represents the set of users that have rated both items i and j.

Best item and *top-N* recommendation problems are the two common problems in recommender systems. The first issue is: finding for a particular user u, the new item $i \in I \setminus I_u$ for which u is most likely to be interested in. When ratings are possible, this task is most often defined as a *regression* or *(multi-class) classification problem* where the aim is to learn a function $f : U \times I \rightarrow S$ that predicts the rating $f(u,i)$ of a user u for a new item i. This function is then used to recommend to the active user u_a an item i^* for which the estimated rating has the highest value:

$$i^* = \underset{j \in I \setminus I_u}{\arg\max}\, f(u_a, j) \tag{1.1}$$

Accuracy is normally used to find the performance of the recommendation method. The ratings R are divided into a *training* set R_{train} used to learn f , and a *test* set R_{test}used to evaluate the prediction accuracy. Two popular measuresof accuracy are the *Mean Absolute Error* (MAE):

$$\text{MAE}(f) = \frac{1}{|R_{test}|} \sum_{r_{ui} \in R_{test}} |f(u,i) - r_{ui}| \tag{1.2}$$

and the *Root Mean Squared Error* (RMSE):

$$\text{RMSE}(f) = \sqrt{\frac{1}{|R_{test}|} \sum_{r_{ui} \in R_{test}} (f(u,i) - r_{ui})^2} \tag{1.3}$$

When ratings are not available, for instance, if only the list of items purchased by each user is known, measuring the rating prediction accuracy is not possible. In such cases, the problem of finding the best item is usually transformed into the task of recommending to an active user u_a a list $L(u_a)$ containing N items likely to interest him or her [40]. The quality of such method can be evaluated by splitting the items of I into a set I_{train}, used to learn L, and a test set I_{test}. Let $T(u) \subset I_u \cap I_{\text{test}}$ be the subset of test items that a user u found relevant. If the user responses are binary, these can be the items that u has rated positively. Otherwise, if only a list of purchased or accessed items is given for each user u, then these items can be used as $T(u)$. The performance of the method is then computed using the measures of *precision* and *recall*:

$$\text{Precision}(L) = \frac{1}{|U|} \sum_{u \in U} |L(u) \cap T(u)| / |L(u)| \tag{1.4}$$

$$\text{Recall}(L) = \frac{1}{|U|} \sum_{u \in U} |L(u) \cap T(u)| / |T(u)| \tag{1.5}$$

1.3.2 Neighborhood-based Recommendation

Neighborhood-based recommendation systems follow the simple principle of *word-of-mouth*, where the opinion of similar people's opinion is considered to decide upon purchase of books, albums, articles or to decide on movies, etc.

1.3.3 User-based Rating Prediction

User-based neighborhood recommendation methods predict the rating r_{ui} of a user u for a new item i using the ratings given to i by users most similar to u, callednearest neighbors. The *k-nearest-neighbors* (k-NN) of u, denoted by $N(u)$, are the k users v with the highest similarity w_{uv} to u. In any case, only the users who have rated item i can predict r_{ui}. $N_i(u)$ is the set of neighbors.The rating r_{ui} can be calculated as:

$$\hat{r}_{ui} = \frac{1}{|N_i(u)|} \sum_{v \in N_i(u)} r_{vi} \tag{1.6}$$

A problem with (1.6) is that it does not consider the fact that the neighbors can have different levels of similarity. Therefore, it is common to normalize these weights, such that the predicted rating becomes

$$\hat{r}_{ui} = \frac{\sum_{v \in N_i(u)} w_{uv} r_{vi}}{\sum_{v \in N_i(u)} |w_{uv}|} \tag{1.7}$$

Equation (1.7) also has an important defect, that it does not consider the fact that users may use different rating values to quantify the same level of appreciation for an item. Different users might give different high ratings for the same item. This problem is solved by converting the neighbors' ratings r_{vi} to normalized ones $h(r_{vi})$ [41], giving the following prediction:

$$\hat{r}_{ui} = h^{-1}\left(\frac{\sum_{v \in N_i(u)} w_{uv} h(r_{vi})}{\sum_{v \in N_i(u)} |w_{uv}|}\right) \tag{1.8}$$

Note that the predicted rating must be converted back to the original scale, hence the h^{-1} in the equation.

1.3.4 User-based Classification

User-based classification gets the most likely rating given by a user *u* to an item *i*, by having the nearest-neighbors of *u* vote on this value. The vote v_{ir} given by the *k*-NN of *u* for the rating $r \in S$ can be got as the sum of the similarity weights of neighbors that have given this rating to *i*:

$$v_{ir} = \sum_{v \in N_i(u)} \delta(r_{vi} = r) w_{uv} \tag{1.9}$$

where $\delta\,(r_{vi} = r)$ is 1 if $r_{vi} = r$, and 0 otherwise. Once this has been calculated for every possible rating value, the predicted rating is simply the value *r* for which v_{ir} is the greatest.

A classification method that uses normalized ratings can also be defined. Let S' be the set of possible normalized values, the predicted rating is obtained as:

$\hat{r}_{ui}$

$$\hat{r}_{ui} = h^{-1}\left(arg\ max_{r \in S'} \sum_{v \in N_i(u)} \delta(r_{vi} = r) w_{uv} \right) \tag{1.10}$$

1.3.5 Item-based Recommendation

While user-based methods rely on the opinion of like-minded users to predict a rating, *item-based approaches* [42] look at ratings given to similar items by the same user. This idea can be stated as follows: Denote by $N_u(i)$ the items rated by user *u* most similar to item *i*. The predicted rating of *u* for *i* is calculated as a weightedaverage of the ratings given by *u* to the items of $N_u(i)$:

$$\hat{r}_{ui} = \frac{\sum_{j \in N_u(i)} w_{ij} r_{uj}}{\sum_{j \in N_u(i)} |w_{ij}|} \tag{1.11}$$

The difference in the users' individual rating scales can be considered by normalizing ratings with a *h*:

$$\hat{r}_{ui} = h^{-1}\left(\frac{\sum_{j \in N_u(i)} w_{ij} h(r_{uj})}{\sum_{j \in N_u(i)} |W_{ij}|} \right) \tag{1.12}$$

The normalized part of this approach can be written as follows:

$$\hat{r}_{ui} = h^{-1}\left(arg\ max_{r \in S'} \sum_{j \in N_u(i)} \delta(r_{uj} = r) w_{ij} \right) \tag{1.13}$$

1.3.6 Similarity Weight Computation

The *similarity weights* play a double role in neighborhood-based recommendation methods: 1) selection of trusted neighbors whose ratings are used in the prediction, and 2) presenting the means to give more or less importance to these neighbors in the prediction. The calculation of the similarity weights is one of the most critical part of building a neighborhood-based recommender system, as it can have a significant impact on both its accuracy and its performance.

1.3.7 Correlation-based similarity

The *similarity* between two objects *a* and *b* can be measured by denoting them as vectors x_a and x_b. Then the *Cosine Vector* (CV) (or *Vector Space*) similarity [43] between these vectors is calculated as

$$\cos(X_a, X_b) = \frac{X_a X_b}{\|X_a\| \|X_b\|} \tag{1.14}$$

The similarity between two users *u* and *v* can be calculated as

$$CV(u,v) = \cos(X_u, X_v) = \frac{\sum_{i \in I_{uv}} r_{ui} r_{vi}}{\sqrt{\sum_{i \in I_u} r_{ui}^2 \sum_{j \in I_v} r_{vj}^2}} \tag{1.15}$$

where I_{uv} once again denotes the items rated by both *u* and *v*. A problem with this formula is that is does not consider the differences in the mean and variance of the ratings made by users *u* and *v*. *Pearson Correlation* (PC) similarity overcomes this issue:

$$PC(u,v) = \frac{\sum_{i \in I_{uv}} (r_{ui} - \bar{r}_u)(r_{vi} - \bar{r}_v)}{\sqrt{\sum_{i \in I_{uv}} (r_{ui} - \bar{r}_u)^2 \sum_{i \in I_{uv}} (r_{vi} - \bar{r}_v)^2}} \tag{1.16}$$

This is different from computing the CV similarity on the *Z*-score normalized ratings, since the standard deviation of the ratings is evaluated only on the common items I_{uv}, not on the entire set of items rated by *u* and *v*, i.e. I_u and I_v. Similar method can be used to obtain similarities between two items *i* and *j* [40, 41], this time by comparing the ratings made by users who have rated both items:

$$PC(i,j) = \frac{\sum_{u \in U_{ij}} (r_{ui} - \bar{r}_i)(r_{uj} - \bar{r}_j)}{\sqrt{\sum_{u \in UU_{ij}} (r_{ui} - \bar{r}_i)^2 \sum_{u \in U_{ij}} (r_{uj} - \bar{r}_j)^2}} \quad (1.17)$$

The sign of a similarity weight reveals whether the correlation is direct or inverse, its magnitude (ranging from 0 to 1) shows the strength of the correlation. Individual user rating scales are different from the item rating scales. And so, it may be more appropriate to compare ratings that are centered on their *user* mean, instead of their *item* mean. The *Adjusted Cosine* (AC) similarity [40], is a modification of the PC item similarity which compares user-mean-centered ratings:

$$AC(i,j) = \frac{\sum_{u \in U_{ij}} (r_{ui} - \bar{r}_u)(r_{uj} - \bar{r}_u)}{\sqrt{\sum_{u \in UU_{ij}} (r_{ui} - \bar{r}_u)^2 \sum_{u \in U_{ij}} (r_{uj} - \bar{r}_u)^2}} \quad (1.18)$$

In the prediction of ratings using an item-based method, it is noticed that AC similarity has been found to outperform PC similarity [40].

IV. CONCLUSION

The detailed survey of the existing literature on the research area has revealed that the Lack of *Personalization* of individual learning is the drawback of most e-learning systems and Tto facilitate personalization of individual learning, there is a need for *adaptive and personalized systems of e-learning.* It was also found that the *Recommender system* is one of the successful existing technology and system available that promotes personalization and recommendations in e-commerce and other domains and Applying recommender systems into the area of e-learning can develop into *e-learning recommender systems* which would very well serve the purpose of personalized e-learning of an individual learner.

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