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Research Article

A Study on Recommendation Categories in Academic D-library

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Abstract: Users increasingly enjoy unprecedented access to varied and huge number of digital resources provided by the academic D-libraries to enrich their education and knowledge. As an academic digital libraries' contents become huger, it is difficult for users to obtain the needed information resources accurately and quickly. Thus, users expect more sophisticated services from digital library systems such as easy to retrieve relevant resources. One effective solution to handle this issue is to make use of recommendation service. The aim of this study is to investigate on the recommender system categories used in academic D-libraries. The paper review the most important categories including collaborative filtering, content filtering and hybrid filtering with their major strengths and limitations. Then, issues and challenges related to these categories are presented, followed by a discussion of solutions proposed by researchers to mitigate these challenges. Finally, based on the survey, a future research possibilities to develop high-quality recommender systems for academic D-libraries is presented.

Keywords: Academic digital library, collaborative filtering, content filtering, hybrid filtering, recommender systems

INTRODUCTION

Academic digital libraries provide information resources and services to faculty and students in academic organizations that support learning, teaching and research (Jange, 2015). The significant amount of digital resources provided by academic D-library opens a number of challenges in the field of academic D-library management of dealing with the overload information and upholding the rising needs expectations of the users (Ambayo, 2010). Regarding these issues, academic D-libraries needed to develop efficient systems that apply personalized services to better meet user's information needs. Personalized service is the process of presenting the right item/service to the right user. The task of delivering personalized services is often framed in terms of a recommendation task in which the system recommends items and services to each user in a different way according to their preferences and needs (Smeaton and Callan, 2005). The idea of the recommendation service is to help users in the effective identification of items suiting their preferences in a large space of possible options by predicting in advance their interest in an item/service (Porcel and Herrera-Viedma, 2009). There are three techniques commonly used in recommender systems based on how recommendations are made, which are collaborative filtering and content-based filtering and hybrid filtering.

Academic digital libraries present a sophisticated, faster, simpler and reliable tool to acquire knowledge in education organizations (Razilan*et al.*, 2009). In (Dollah, 2008) the importance of the role of academic digital libraries in the dissemination of knowledge is emphasized to increase the users' knowledge in academic institutions. Adeniran mentions that the use of electronic resources in the libraries is necessary for universities development (Adeniran, 2013). There are benefits that academic digital library can provide in education:

- Creation of an environment which contribute to faculty and students research (Recker *et al.*, 2007).
- Provide an easy tool for students to find relevant information to their courses (Adeniran, 2013).
- Curriculum planning (Maull *et al.*, 2010).
- Designing teachers' courses (course development) (Barker, 2009).
- Help in distance learning and e-learning university programs (Sharifabadi, 2006).
- Teachers can share resources in ways that are not practical with paper-based resources (Impagliazzo *et al.*, 2003).

The article contributions are two-fold:

- First, it discusses solutions proposed by researchers to address recommender systems' challenges.

- Second, it presents future research opportunities that can help to alleviate the challenges Cold-start, Sparsity, Grey-sheep and Scalability.

LITERATURE REVIEW

Recommender system is a software which helps users in finding items in a large space of possible options suiting their preferences (Mönnich and Spiering, 2008). According to (Malinowski *et al*., 2008) a recommender system could be seen as a decision support system, where the solution alternatives are the items to be recommended and the criteria to satisfy are the user preferences. Such systems have become powerful tools in many domains, such as, e-commerce (Castro-Schez *et al*., 2011), social network (Guy *et al*., 2010), tourism (Zhao and Ji, 2013), digital library (Tejeda-Lorente *et al*., 2014a) and so on.

Role of Recommender systems in academic D-library:

- To satisfy the user's requirements and their needs.
- To access relevant information very quickly.

The recommender system architecture usually compose of:

- Background data, which is the information the system has been generating recommendations earlier,
- Input data, the information that has to be entered in order to begin the process of recommendation,
- An algorithm that combines the background data and input data to produce recommendations.

Since the provision of recommender systems requires a thorough knowledge of users' preferences (Tejeda-Lorente *et al*., 2014a). This knowledge implies that the system present user actual interest in the form of a profile (Ambayo, 2010). The authors emphasized that successful recommendations mainly depend on accurate users' profiles (Quiroga and Mostafa, 2002). The user profile can be built in different ways; one way can bebuild based on demographic information (Chen and Chen, 2007). Another way can be built by utilizing preference information, such as services or items in which the user is interested, this type of profiles is called the user interest profile (Adomavicius and Tuzhilin, 2005). In principle, there are two types of the user interest profile:

- Profiles based on explicit feedback. Explicit feedback is provided by users when they are asked to evaluate services or items (Li *et al*., 2010). Explicit feedback usually performs the feedback as a numeric rating scale or a binary like/dislike rating. Explicit feedback has the advantage of simplicity, recommender systems can easily use it and it is often well understood by users. Nevertheless, explicit feedback results in a static user profile, which is suitable for the recommendation process for some time after it is built; but its performance degrades over time as the profile ages (Bhide *et al*., 2007).
- Profiles based on implicit feedback. Implicit feedback is inferred from user behaviour as they interact with the system. Using implicit feedback provides many benefits:

  - Provide data without any additional burden on the users (Rendle *et al*., 2009)
  - It is immediately available (Pohl, 2006)
  - Provides better coverage than explicit data (Jawaheer *et al*., 2014)
  - More reliable than explicit feedback as users provide their interest without they are aware (Schafer *et al*., 2007)

There are three main approaches that have been used to perform recommendation, namely, content-based filtering, collaborative filtering and hybrid filtering:

- Content-based filtering approach also called item-to-item correlation approach (Li *et al*., 2009).
- Collaborative filtering approach sometimes called the social-based approach (Yang *et al*., 2006) or user-to-user correlation approach (Li *et al*., 2009).
- Hybrid filtering approach this approach combines multiple recommendations approaches together to produce its output.

In addition to these three approaches, there are two other approaches that have been used to perform recommendations, they are:

- Demographic filtering approach this approach provides recommendations based on the demographic profile of the active user (Pazzani, 1999). Its advantage is that the user's history data is not needed, so a new user can obtain recommendation (Wang *et al*., 2012). Since the Demographic approach is based on the demographic user's profile if the active user's demographic information is not available, it is not possible to recommend items to the active user (Adomavicius and Tuzhilin, 2005).
- **Knowledge-based filtering approach:** This kind of approach recommend objects based on inferences about users' preferences and needs (Burke, 2002). This approach sometimes provides explicit knowledge about how the recommended items meet the users' preferences (Tejeda-Lorente *et al*., 2014b).

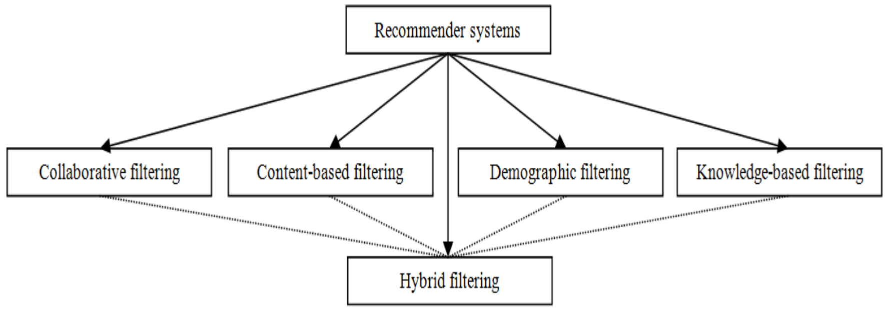

Fig. 1: Recommender approaches

Figure 1 shows approaches of recommender systems.

Usually, recommender systems rely on collaborative filtering approach, content-based filtering approach and hybrid filtering approach, in the next sub-sections more reviews on these approaches are presented.

Collaborative filtering approach: In this approach, the system collects and analyzes a large amount of information on users' preferences and determine recommendations to a target user based on their similarity to other users who are called nearest-neighbour(Su and Khoshgoftaar, 2009).The input for systems that are based on collaborative filtering approach depends only on the item and user identifiers and ignore user attributes (e.g., demographics) and item attributes (Schein *et al*., 2002).

In describing the collaborative filtering approach model, four steps are followed to recommend resources to an active user:

Input: An active user profile and previous users' profiles
Output: A set of resources in descending order
Step 1: Matching target user profile against previous users' profiles to find a set of users known as neighbours, i.e., most similar users
Step 2: Calculate the prediction rating for the resources most liked by the top nearest neighbours
Step 3: Sort the resources in a descending order based
Step 4: Select the top-N resources as the recommendation list.

The collaborative approach has the capability to recommend items that are not limited to similar items that active users have liked in the past (Li *et al*., 2009). In addition, it does not depend on the availability of textual descriptions (Billsus and Pazzani, 1998). Therefore it has the capability of recommending complex items such as movies without requiring an "understanding" of the item itself.

Figure 2 illustrates the collaborative filtering model process.

Since the collaborative approach is based on the user activities they have the following limitations:

- New items cannot be recommended to users until they have been rated by others. This problem is called the first-ratter problem or Cold-start problem (Lika *et al*., 2014).
- Rating a very small portion of items by users leads to the lack of overlap of preferences between users and therefore makes it difficult to define neighbourhoods. This problem is called the Sparsity problem (Li *et al*., 2009).
- As the number of users and items increases, the computation time to calculate the similarity between users grows linearly resulting in poor scalability (Sarwar *et al*., 2000).
- The approach is biased towards the most popular items, i.e., items which have been rated by many users are more likely to be recommended than items that have few ratings (Adomavicius and Tuzhilin, 2005).

Research on collaborative filtering can be grouped into two methods: memory-based and model-based (Christidis and Mentzas, 2013). Memory-based methods (also calledneighbourhood-based) make similarity comparison across the entire user's historical database to find out the most similar users to the active user and then, recommendations are generated based on the similar users' rating. Notable memory-based algorithms include the Pearson Correlation algorithm (Popescul *et al*., 2001), the Vector Space Similarity algorithm (Breese *et al*., 1998) and the Extended Generalized Vector-space algorithm (Soboroff and Nicholas, 2000). Different from memory-based methods, model-based methods requires constructing a descriptive model of users using the user-item ratings and then recommendations are predicted using this descriptive model. The common methods of this type include "Regression Analysis", "Association Rule", "Clustering methods" and "Bayesian Network". Recommendation systems based on association mining

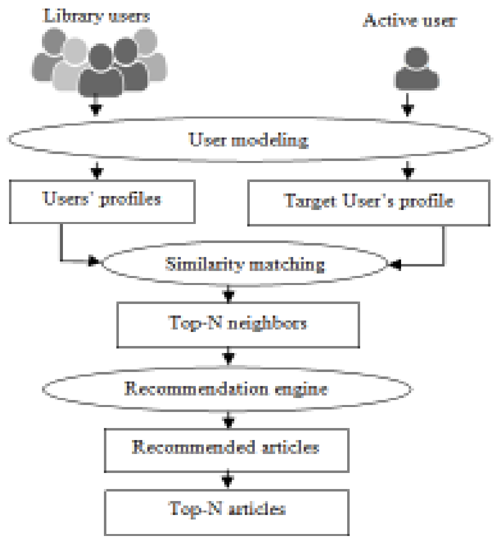

Fig.2: Model of collaborative filtering approach process

are very popular in collaborative filtering D-library systems, e.g., (Li and Chen, 2008) and (Zhu and Wang, 2007). In addition of using association rule mining, sequential pattern mining technique was applied in collaborative filtering D-library systems, e.g., (Sitanggang *et al*., 2010). The studies in (Lina and Zhiyong, 2013) and (Chen and Chen, 2007) combine clustering mining and association rule mining. The purpose of using clustering technique is to reduce the search space. Thus, computing recommendations will be faster than scanning the entire database and predictions for recommendations are computed independently within each cluster which improves the quality of recommendations. With the fast development of social networks, social data played an important role in collaborative filtering to find relevant information (Beierle *et al*., 2016). Social networks represent a viable information source for recommender systems to produce more reliable recommendation (Akbar *et al*., 2014). Usually, collaborative filtering recommender systems depend on users' ratings for building models for providing recommendations, in the absence of ratings and user profiles, recommender systems based on social networks used social relations for building models (Akbar *et al*., 2014; Beierle *et al*., 2016).

Memory-based collaborative filtering methods are more resource intensive than model-based filtering methods (Lemire and Maclachlan, 2005). Model-based collaborative filtering methods can produce more precision recommendations and achieve good online performance in comparison with memory-based collaborative filtering methods (Sushmitha *et al*., 2015).

Memory-based and model-based algorithms have two kinds of approaches: item-based and user-based. The item-based approach recommends items based on its similarity to the ones the active user preferred in the past (Miller *et al*., 2004). The user-based approach analyzesa large amount of information on users' preferences and determines recommendations to a target user based on other users that have similar interests (Im and Hars, 2007).

Content-based filtering approach: This approach recommends an item to a user based on item's features and a profile of the user's interests (Pazzani and Billsus, 2007).

The process of the content-based approach model is described as follows:

Input: An active user profile and descriptions of articles
Output: A set of resources in a descending order
Step 1: Compare the target user profile with the features of the articles
Step 2: Selects the most valuable articles based on the comparison between the active user profile and features of the articles
Step 3: Sort the resources in a descending order based
Step 4: Select the top-N resources as the recommendation list.

Content-based filtering model process is depicted in Fig. 3.

As the content-based approach does not depend on the user ratings, it has the following advantages (Dong *et al*., 2009):

- Does not suffer from Cold-start problem
- Does not suffer from Sparsity problem

On the other hand, the content-based approach has the following limitations:

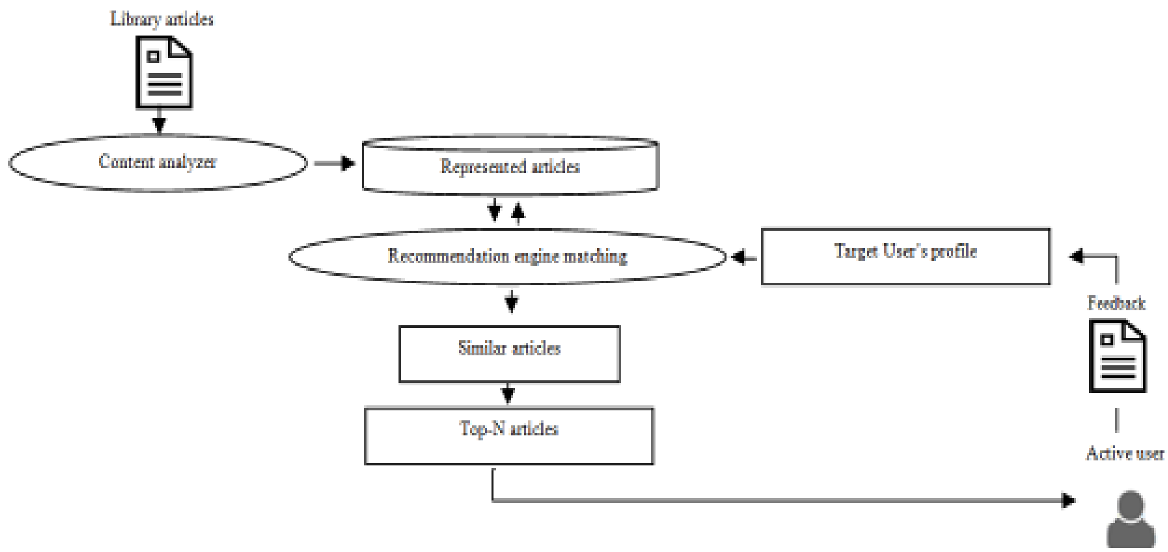

Fig. 3: Model of content-based filtering approach process

- It ignores the popularity of items (Dong *et al*., 2009).
- In the domain of media, including sound, picture and video the approach faces the problem calculating the similarity among items (Democvic *et al*., 2013).
- It is difficult for most content-based methods to find out the relationship between different names but describing the same item, i.e., many items have different names in real life. This problem is called the Synonymy problem (Shardanand and Maes, 1995).

The content-basedapproach in academic digital libraries takes various approaches for the recommendation process. One approach is based on task-focused approach (Hwang *et al*., 2003). The task-focused recommendation requires a user to specify a task profile which includes a small set of documents that the user recently accessed to build the task profile. The system recommends articles that it contents are similar and/or that are often accessed together with the articles included in the task profile. Another type of content-based approach is based on the resource's main ideas (Hanyurwimfura *et al*., 2015), these types of systems will not be a reliable solution if the resource's topics or the main ideas are not well formulated. Citation data is used in the content-based approaches an indicator of relatedness between documents in the content-based approach to recommend resources (McNee *et al*., 2002), e.g., (Liang *et al*., 2011a; Liang *et al*., 2011b; Strohman *et al*., 2007). Unfortunately, citation-based approach has two problems:

- Extracting citations from articles is a costly process
- New published articles needs considerable time to collect a sufficient number of citations for conducting meaningfulstatistical analysis (Pohl *et al*., 2007).

Hybrid filtering approach: Using a hybrid approach helps to avoid certain limitations of recommendations approaches and gives more effective recommendations in some cases (Adomavicius and Tuzhilin, 2005; Porcel and Herrera-Viedma, 2009). The limitation of this approach is that it demands more information compares to content-based approach or collaborative approach (Li *et al*., 2009). Different recommendation approaches can be combined in many ways, i.e., Content-based, Collaborative, Knowledge-based and Demographic. The most common hybridizing methodology used in academic D-library recommender systems is combining content-based approach and collaborative approach.

The following list describes the hybridization techniques that can be used to merge content-based approach and collaborative approach (Tiwalola and Asafe, 2015):

- **Weighted hybrid:** Weighted hybrid derives recommendations by combining the scores for each item computed by individual recommenders into one score.
- **Mixed hybrid:** This technique is based on merging recommendations generated from each component into one ranked list.
- **Switching hybrid:** Switching hybrid technique allow the system to switch between components of the system according to the situation is based on the idea that according to the situation of the system.
- **Feature combination hybrid:** This technique only employs one component of the hybrid recommender system named actual recommender which is supported by a second passive component

named contributor recommender. The contributor recommender injects its features into the algorithm of the actual recommender.

- **Feature augmentation hybrid:** This technique is similar to the feature combination hybrid technique, but instead of using raw features from the contributor component, new features generated by a learned model are used for input to the actual recommender.
- **Cascade hybrid:** In the cascade hybrid technique several techniques sequentially are executed. The primary component recommendations used as input to the secondary component, then the secondary recommender is employed to refinements these recommendations.
- **Meta-Level hybrid:** This technique also employs actual andcontributor recommenders but instead of supplying the actual recommender with additional features, meta-Level hybrid provides the entire model as input to the actual recommender algorithm.

ISSUES AND CHALLENGES

The recommender systems challenges that should be considered when designing recommender systems are stated as follows (Khusro *et al*., 2016; Tiwalola and Asafe, 2015):

Privacy: Demographic information about users may lead to data privacy issues.

Cold start problem: This problem arises when new resources or users are just added to the catalogue. Hence there is very less information about these resources or users. In such cases, it is very difficult for recommender systems to predict effective recommendations.

Synonymy: This problem occurs when more than different names with similar meaning are given to the same item. In such case, the recommender system cannot identify if these names represent one item or different items.

Sparsity: This problem occurs when most users do not rate most items. As the collaborative filtering process is based on computing similarity over the users to find similar users, sparse rating makes it difficult to find similarity between users.

Scalability: With the enormous growth of users and items it becomes difficult for collaborative filtering recommender systems to process such huge-scale data.

Shilling attacks: Competitors or malicious users give false ratings on items trying to increase or decrease item popularity. This may lead to decrease the quality of the prediction for many items. Detecting and removing attack profiles is a greatsignificant to ensure the trustworthiness of recommender systems.

Limited content and over-specialization problem: The limited availability of content about items and users leads to problems including over-specialization problem. Over-specialization problem restricts the users with their profiles, thus preventing the recommender system to provide the users new items.

Grey sheep: The grey sheep problem occurs in collaborative filtering systems where users' opinions do not match with any group of users and, therefore, are unable to get benefit from collaborative filtering.

Table 1: Challenges and proposed solutions

Challenge	Category	Proposed solutions
Cold-start	Collaborative filtering approach	Using demographic information (Agarwal*et al*., 2017) Asking new users explicitly to rate some items (Nadimi-Shahrak and Bahadorpour, 2014)
Scalability	Collaborative filtering approach	Using clustering algorithms (Su and Khoshgoftaar, 2009) Using dimensionality reduction techniques (Su and Khoshgoftaar, 2009)
Sparsity	Collaborative filtering approach	Using demographic information (Grčar*et al*., 2006) Using dimensionality reduction techniques (Grčar*et al*., 2006)
Gray sheep	Collaborative filtering approach, Demographic-based approach	Integrating content-based filtering with collaborative filtering techniques (Su and Khoshgoftaar, 2009)
Privacy	Collaborative filtering approach, Demographic-based approach	Privacy-protection techniques can be applied include (Jeckmans*et al*., 2013) Cryptographic mechanisms Randomized perturbation techniques
Synonym	Collaborative filtering approach	Using dimensionality reduction techniques (Sarwar*et al*., 2002)
Limited content analysis and over-specialization problem	Content-based filtering approach	Integrating content-based filtering with collaborative filtering techniques (Jain*et al*., 2015) Genetic algorithms (Prabha and Duraisamy, 2016)
Shilling Attacks	Collaborative filtering approach	Using detection methods (Bilge*et al*., 2014)

Table 2: Proposed solutions' drawbacks

Proposed solutions	Drawbacks
To overcome the Cold-start and Sparsityproblems, use of demographic information is proposed.	The users' demographic information should be updated periodically otherwise the system will give static suggestions. Gathering demographic information may lead to privacy issues.
Several researchers have suggested the mechanism "asking new users to rate some items" to avoid the Cold-start problem.	It is suitable for the recommendation process for some time after it built the profile, but its performance degrades over time as the profile ages. Increase the burden on users.
Clustering algorithm is the most solution used to solve Scalability problem.	This approach has limitation that it suggests resources only related to users in one cluster, thus, limiting the number of predictions that can be provided for clustered users.
Dimensionality reduction techniques were used to overcome the Scalability and Sparsity and Synonym problems.	Useful data can be discarded instead of irrelevant data, this decrease the prediction quality. Leads to data hard to interpret.
Several researchers have suggested a hybrid system to resolve the grey sheep and limited content analysis and over-specialization problem.	It increases the complexity, and it is expensive to implement.
Many recommender systems have used privacy-protection techniques, including Cryptographic mechanisms and Randomized perturbation techniques to protect users' data.	Cryptographic techniques are extremely slow. Cryptographic techniques suffer from heavy computational overload when dealing with a large dataset. Randomized perturbation techniques induce large noise which leads to low-quality predictions.
Genetic algorithms have been widely applied to solve the limited content analysis and over-specialization problem.	It requires a long time to run. Representation of the algorithm may be difficult.
To overcome theshilling attackschallenge, detection methods are proposed.	Suffer from misjudgment of normal users. This lead to removing rating given by normal users. Most detection techniques are developed based on a certain type of attacks. Hence, these techniques do not fit various shilling attack types.

Evaluation: Evaluation is crucial for proving the quality of a recommender system. Selecting the suitable evaluation metrics is a key problem in recommendation systems. The available evaluation metrics, i.e., MAE, Precision, recall and F-Measure are general-purpose metrics. Another issue related to recommender system evaluation, the majority of existing datasets is proprietary datasets and therefore, cannot be used for benchmarking.

Table 1 presents the above-motioned challenges and the approaches that suffer from it as well as some proposed solutions and techniques that were proposed to cope with these challenges.

DISCUSSION

The proposed solutions mentioned in Table 1 are no doubt overcomes all of the recommender systems challenges. However, with its benefits, come some drawbacks as well, Table 2 presents the proposed solutions along with their drawbacks.

FUTURE TRENDS

Based on recommender systems challenges, this section presents some future research opportunities for academic D-library recommender systems that can help in mitigating Cold-start, Scalability, Grey-sheep and Sparsity challenges.

Implicit feedback: In a collaborative filtering recommender system, feedback is required to identify users' preferences. Implicit feedback takes advantage of user behaviour to generate relevance feedback to enrich the user profile. The implicit feedback method provides much larger quantities of data rather than the sparseness encountered by explicit user feedback. This method could alleviate the Sparsity problem.

Educational social network for university: Education social networks are used by university students for study purpose. In our view, there is a possibility of engaging education, social networks in D-library recommender systems. The idea is to apply the concept of social recommenders in D-library recommender systems. Education social networks contain groups of students. A group is a feature in the education social networks that allow students to meet students with similar interests. With this feature, relevant information can be provided to students. Recommender systems can handle the Cold-start, Scalability and Grey-sheep problems by engaging the educational social networks as follow:

- Any student joins a group will find at least one student in the group. Thus, the preferences information about the new student can be obtained from this group. This can avoid Cold-start problem.
- Any student may belong to many different groups: software engineering group, data structure group, system analysis group, etc. Grouping mechanism

will reduce the search space, thus computing recommendations will be faster than scanning the entire database this will handle the Scalability problem. Grouping mechanism is better than clustering approach because the grouping mechanism recommendations cover resources from different areas, i.e., user can get recommendations according to their groups, whereas the clustering approach suggests resources related to a limited number of users.

- The recommendations can be maintained for the target user according to the preferences of the most group the user reacts with it. This can handle the Grey sheep problem.

CONCLUSION

Academic libraries became resource centres for education and research. Nowadays, academic libraries content a huge amount of information resources, such as electronic journals, electronic books and electronic papers. These information resources are growing up which overwhelms users and makes it difficult for them to access to relevant information. This huge number of resources provides opportunities to users, at the same time, users have to face the problem of the overload information which affects the efficiency of information seeking and lead to waste time during the usage of the digital library. This has raised the importance of the recommender systems in academic D-libraries. The main focused on this study was exploring the categories of recommender systems used in academic D-libraries. The paper presents the challenges which face recommender systems and proposed solution by researchers to cope with these challenges. The paper also proposes some future trends to guide new researchers to mitigate with the challenges Sparsity, Scalability, Grey sheep and Cold-start.

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