A Hybrid Approach for Thread Recommendation in MOOC Forums

Ahmad. A. Kardan, Amir Narimani, Foozhan Ataiefard

***Abstract*—**Recommender Systems have been developed to provide contents and services compatible to users based on their behaviors and interests. Due to information overload in online discussion forums and users diverse interests, recommending relative topics and threads is considered to be helpful for improving the ease of forum usage. In order to lead learners to find relevant information in educational forums, recommendations are even more needed. We present a hybrid thread recommender system for MOOC forums by applying social network analysis and association rule mining techniques. Initial results indicate that the proposed recommender system performs comparatively well with regard to limited available data from users' previous posts in the forum.

***Keywords*—**Association rule mining, hybrid recommender system, massive open online courses, MOOCs, social network analysis.

I. Introduction

ONLINE question and answer (Q&A) forums have been developed to provide an environment for users to ask their questions and problems in different areas. Forums have become more popular due to the vast amount of knowledge and expertise sharing in the simple way of asking and answering. Knowledge shared in forums is usually very broad and categorized through different threads, which contains questions and answers about similar topics. Take for instance Yahoo Answers, one of the largest Q&A forums in English, includes 26 top-level and 1002 (continually expanding) low-level categories divided into multiple threads. Due to the fast growth of forums, finding relevant threads for asking questions and exploring similar solutions for ones' problem has become more difficult. This issue is considered to be more important in online learning systems such as Coursera and edX, where discussion forums are the most indispensable elements for instructors and students to ask questions, discuss ideas and look into some possible relative answers. Also, problem solving is done by students themselves, because it is almost impossible for course instructors to address all questions that are raised in forums. Due to a large number of students in the mentioned systems, threads per every course forum expand very quickly and consequently it becomes more complicated for students to find topics that they truly look for.

Recommender systems have been created to deal with the information overload problem in forums [1], [2]. The objective of these recommender systems is to create meaningful recommendations to a collection of users for items or threads that might interest them. Recommending relative and suitable forum threads to students of a massive open online course (MOOC) system is a topic to be considered more carefully. It is due to the fact that, student drop toward the end of the course schedule increases [3]. This drop is mainly because learners feel that course materials become more complex as course advances and in exam time they will not perform good enough to get fitting scores. Exploring students' contribution and interest to different threads of course forums helps instructors to comprehend course progress and students need for specific support [4]. So, relevant thread recommendation comes handy when this need for support is perceived to improve students' overall performance.

Traditional recommender systems commonly used collaborative filtering and content-based recommendation approaches. While collaborative filtering techniques try to extract user-item relations based on users previous behaviors as well as similar users ratings, content-based techniques recommend items similar to the ones that have been liked or visited by the user. It has been demonstrated that combining these two approaches can lead to more successful recommendations of threads or answerers in discussion forums [5]. We try to design a hybrid recommender system that combines the aforementioned approaches in order to recommend relevant threads to MOOC forum users. We map user contribution in forums to social networks and analyze these networks to discover similar users for collaborative filtering purposes. Also, association rule mining is employed to find threads relevant to those a user has posted on.

The rest of this paper is organized as follows. In the next section, we briefly introduce recommender systems with a main focus on thread recommendation. Related works to social network analysis and association rule mining are introduced in this section as well. In Section III, we describe our hybrid recommender system architecture. In Section IV, implementation of proposed recommender system is explained to clarify steps toward recommendation by a sample data. Then, we evaluate the performance of our system by using extensive dataset of Coursera forum posts on three different courses in Section V. Finally, conclusions and directions for future studies are provided in Section VI.

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II. Related Works

Nowadays, Recommender systems are considered as an efficient solution for users to prevent the confusion from the massive information available on the Internet. In fact, recommender systems recognize relevance between users' profile information and specific contents. To our knowledge, various approaches for recommender systems have been discussed in previous articles [6], from which we will discuss recommendation techniques that our research benefits from mostly. It is appropriate to categorize most of the recommendation problems into two general types of recommendation filtering: Collaborative filtering and content-based filtering [7].

Collaborative filtering makes recommendations based on similarities between a user and another active user who currently has a generated recommendation. It also finds similar users by finding groups of users who share common interests. Different applications to explore users' interests and opinions are introduced in studies published by Yin et al. [8]. As an instance, user similarity discovered based on expanded observation time for a specific item by different users, Iaquinta et al. [9], and also uses rating scores to the items based on a defined scale. Despite the fact that collaborative recommendation is the most used filtering technique among others, it has some disadvantages. A major drawback of this approach is assigning new users into existing groups, namely cold start [10].

On the other hand, content-based recommendation creates user profiles based on any individual user's favorite contents. In general, it extracts important specifications about the items that user is interested in, and then recommends similar items to a user according to these features. In a study published by Li et al. [11], a content-based recommendation technique is introduced applicable to discussion forums based on users' authority. In this approach, underlying factors for computation of users' authority in a discussion group are users' activity, social network and a total number of users' posts. There are some examples of content-based recommendation approaches that consider user preferences and behaviors [12], and users' liked and disliked posts [13], to discover the relation between items. The principal advantage of the content-based filtering approach is in its nature: it can start to recommend as soon as there is information about available items. However, recommendations are based on the items' attributes, descriptions, and tags; therefore, any user personality assessment is missing.

To tackle problems related to content-based and collaborative filtering recommendations, hybrid recommender systems utilized recently, benefits from both of these approaches [14]. So when gathered information on an item is inadequate, collaborative technique takes over and fills the recommendation gaps of content-based recommendation. In the same way, in situations that extracted features about an item or user are insufficient, the content-based technique supports the recommendation system and solves the problem. The proposed recommender systems, especially the ones employed in discussion forums, require prepared information about thread topics, posts content or user profiles to make recommendations [5].

In order to study discussion forum dynamics, social network analysis is proposed by many studies. One of the most common methods for mapping user posts to a social network is by using bipartite graphs that are exploited in related papers [15]. Two different sets of nodes form the social network, users, and threads. A directed edge will be created for each post by a user in a specific thread. The direction of the edge is considered to be from user to thread and we can weigh these edges based on a number of a user's posts in a specific thread. So, we can assess activity level of a user based on simple social network metrics like outdegree. Another method to create a social network is to consider users as nodes and directed edges from asker to replier. By utilizing this method, Adamic et al. Reference [16] explored Yahoo Answers forum comprehensively and categorized threads based on their topics. These categories studied by degree distribution, ego network analysis, motif analysis and connected components. They showed forums of various topic categories have different types of social network specifics.

Association rule mining has become an important data mining technique employed by numerous recommender systems in various fields [17]. These recommendations rely on the frequency of itemsets appearance in a transaction database. A mined rule like $X \rightarrow Y$ indicates that when a transaction includes itemset X it will include itemset Y by a predefined probability. Measures like support and confidence introduced to control range of the probability based on desired values of different applications. Support of a rule like $X \rightarrow Y$ counts the number of transactions which include X and Y in a database and divides it to the size of the database. Also, in a given transaction database, confidence value of a discovered rule shows the ratio of transactions that contains both X and Y simultaneously to those that includes X.

Prior works have discussed the importance of successful forums for better MOOC courses [4], [18]. One major problem of MOOCs described as dropout behavior of learners towards the last weeks of a course schedule. Course recommendations beside thread recommendations introduced as effective means to guide students through learning steps [19]. However, these systems require specific knowledge about users' prior activity in details and content of every post in threads to be employed. Lack of a thread recommendation system, which can perform with available data of learners' posts from course first few weeks, is obvious in prior researches.

III. Description of Hybrid Recommender System

As discussed in previous sections, hybrid recommender systems have been more popular for thread recommendation purposes, where we have to discover both similar users and relevant threads. Our proposed system to make hybrid thread recommendations is based on social network analysis and association rule mining techniques which will be explained in this section. By exploring forums social network, we try to add collaborative filtering features to recommendations discovered by association rule mining. Fig. 1 shows the overall architecture of the proposed system, composed of two main parts, namely social network analysis of user posts and association rule mining of threads.

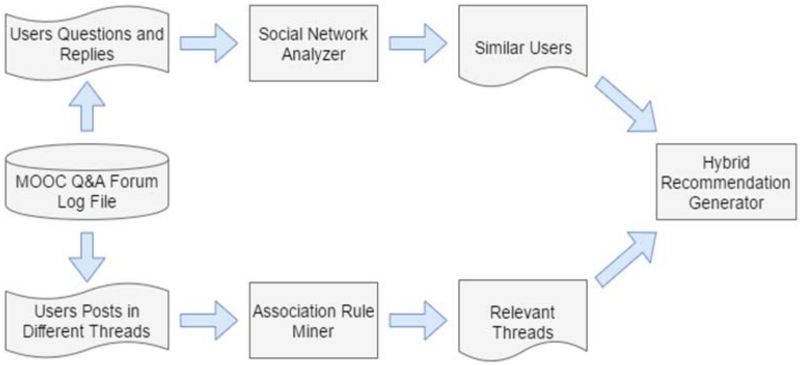
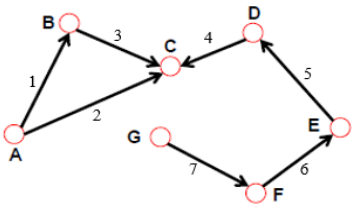


Fig. 1 Architecture of proposed hybrid recommender system

Social Network Analysis subsystem attempts to identify users with similar interests and related threads with a high number of posts, whereas association rule mining subsystem tries to find threads that different users commonly have posted on.

In Q&A forums a user creates a thread with an initiative question and other users provide some responses to the question. Different methods are possible to map these forum dynamics to social networks, which discussed in related works. Fig. 2 illustrates the described way of creating social networks from a sample forum data.



Post ID	Asker	Replier
1	A	B
2	A	C
3	B	C
4	D	C
5	E	D
6	F	E
7	G	F

Fig. 2 Illustration of employed method for creating social network from sample data

We exploited the method that each node represents an active course student and every directed edge represents an answer from asker to replier. In doing so, we can differentiate between students who are looking for information on a course topic (by considering outdegree), and also students that already are familiar with the topic and can provide possible answers (by considering indegree). Additionally, we can discover node modules with similar users, using community detection in social network analysis tools (like Gephi). Learners identified in the same modules are likely to have common interests. So, we classify learners based on their outdegree to indegree ratio and their community in social networks. New users with a few posts cannot be categorized precisely by degree measure. In this case, communities are utilized to provide estimation about new users. So, cold start problem related to many recommender systems dissolved automatically.

The second part of the proposed hybrid recommender system to discover related threads is based on association rule mining. As discussed in the previous section, association rule mining techniques are used widely for recommendation purposes [5], [17]. The two main metrics of association rule mining, namely *support* and *confidence*, are flexible measures, which can vary based on how precise or how much recommendations are desired.

In our proposed method, threads are considered as items and a specific user contribution in different threads creates initial itemsets (referred as market basket in previous studies). Applying association rule mining, we discover thread groups that users have posted on. Every thread subset from these groups, with specific *support* and *confidence* value, can be a recommendation nominee for similar users (discovered by social network analysis) to the ones that posted on these threads.

Consider a rule like $\{X, Y\} \rightarrow Z$ discovered. This rule indicates that users (e.g., {U1, U2, U3}) who posted on X and Y threads are probably posted on thread Z based on minimum confidence value. The proposed system can offer two types of recommendations. First, it can recommend thread Z to the users that posted on X and Y but did not post on Z. The second type, which is more complex, recommends thread Z to users that are considered similar to the ones posted on X and Y. The second type contains the concept of hybrid recommendation based on content-based filtering and collaborative filtering approaches.

IV. Implementation of Proposed Hybrid Recommender System

In this section, we describe implementing the proposed recommender system using data gathered from different forums of Coursera [20]. This data includes thread posts of 60 different courses presented in Coursera. Information about 739,075 posts (e.g., post_id, post_thread, user_id, forum_id, post_time) are available to explore thread dynamics. We examined different courses and students' posts on forum threads. To illustrate steps explained in the previous section, we choose *Blended Learning* (Personalizing Education for Students) course. A total number of 358 different users and 2352 unique posts mapped into a social network. As described in the previous section, directed edge illustrates a post from asker to replier. In this case, edge weights indicate a number of answers between two specific students. So, we have 1044 different edges in the network. Figs. 3 and 4 show the social network of *Blended Learning* course forum with node size representing its relative outdegree and indegree measure respectively.

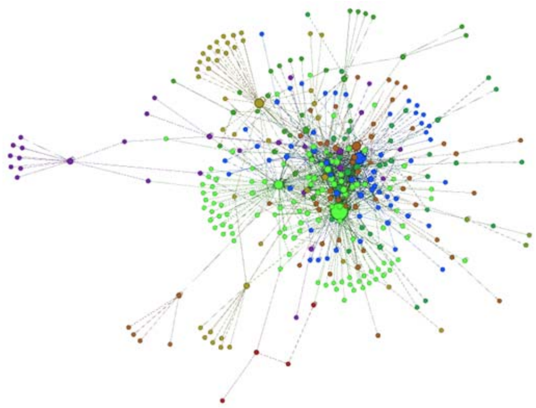


Fig. 3 Social network of Blended Learning course forum based on outdegree

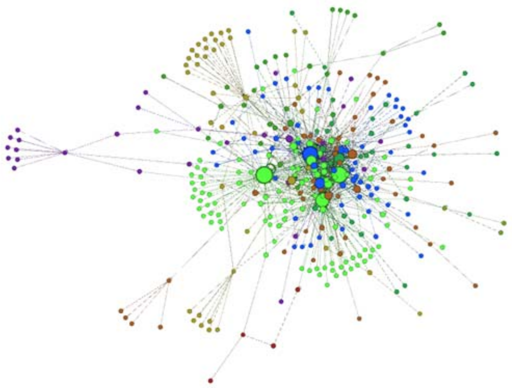


Fig. 4 Social network of Blended Learning course forum based on indegree

Larger nodes in Fig. 3 indicate users who have more questions in the course forum. Likewise, larger nodes in Fig. 4 indicate users that posted more replies in the forum. We categorized users of *Blended Learning* on three groups (*G1*, *G2*, and *G3*) based on their weighted outdegree to indegree ratio (*WOIR*). Equation (1) utilized to define *WOIR* where *U* is a user:

$$WOIR = \frac{Weighted\_Outdegree(U)}{Weighted\_Indegree(U)} \tag{1}$$

Users in *G1* are replier type and their *WOIR* is lower than 0.25. The total number of users in *Blended Learning G1* is 193. Users with *WOIR* between 0.25 and 1.5 form *G2* (123 members). Users with *WOIR* higher than 1.5 are more asker (initiator type) and grouped in *G3* (42 members). We prioritize recommendations within the same type of groups, but we will examine recommendations accuracy in different groups and among them in the next section.

Also in Figs. 3 and 4, nodes with the same color belong to same communities and their activities are mostly in the same threads. Thirteen different communities were detected in the *Blended Learning* forum with resolution 1.0 based on algorithms used by Gephi [21], [22]. Fig. 5 illustrates the proportion of each community size based on node counts relative to the whole social network.

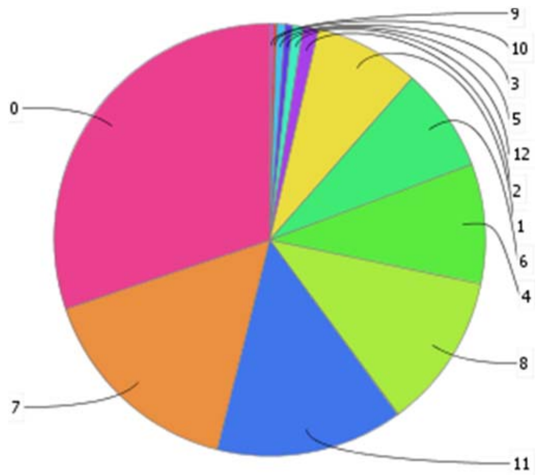


Fig. 5 Proportion of community size to Blended Learning Social Network

After categorizing user types and detecting communities, we study the activity of every user in the threads. According to the basics of association rule mining, we considered each poster on a thread as user and threads as items. Association rule mining with different *support* and *confidence* employed via FP-growth algorithm [23]. As an instance, with minimum *support* 0.005 and *confidence* 0.1 thresholds some rules discovered. Table I shows discovered rules with their *support*, *confidence* and *lift* values.

TABLE I
ASSOCIATION RULES FOR BLENDED LEARNING COURSE

Association Rule	Support	Confidence	Lift
T0001→T0092	0.011	0.104	1.366
T0092→T0001	0.011	0.148	1.366
T0001→T0002	0.021	0.190	1.982
T0002→T0001	0.021	0.215	1.982
T4039→T3257	0.005	0.225	13.092
T4039→T0002	0.006	0.254	2.650
T3257→T4039	0.005	0.308	13.092

Compared to previous studies, minimum *support* of 0.005 and *confidence* of 0.1 are highly acceptable [5]. *Lift* measure is calculated to indicate the quality of discovered rules. Additionally, we can map discovered association rules of large databases into a bipartite graph. This allows us to explore numerous association rules of large databases more conveniently. Graph of rules from Table I is shown in Fig. 6.

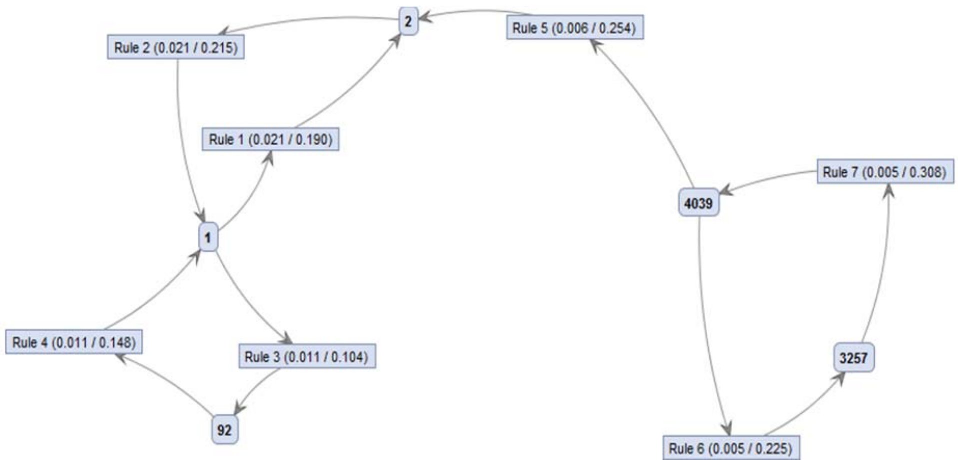


Fig. 6 Bipartite graph illustration of discovered association rules from Table I

After mining association rules, we can recommend relevant threads to users similar to the ones contributed on these threads. For example, the user identified by ID *U6368224696* has contributed in threads *T0001* and *T0092*. Also, this user has *WOIR* equal to 0.5 and is in group *G2*. Besides, this user belongs to the community with identifier 0 (in Fig. 5). Our proposed system recommends *T0001* to users in the same community and with similar *WOIR* range to *U6368224696*, who has posted on thread *T0092*. Likewise, for users with post on *T0001* and similar to *U6368224696* thread *T0092* is recommended.

V. Results and Evaluations

In the evaluation of user posts on different threads, we have four different outcomes. Table II illustrates possible outcomes based on threads.

TABLE II
Possible Outcomes of Thread Recommendation

	Recommended Thread	Not Recommended Thread
User has posted	True-Positive (TP)	False-Negative (FN)
User has not posted	False-Positive (FP)	True-Negative (TN)

Metrics extensively used for recommendation purposes can be derived from these outcomes where evaluated data is static [24]. For every user, we can count each cell value from Table II, and then compute total quantities of each cell. *Precision* and *Recall* measures can be calculated for recommender systems with (2) and (3):

$$Precision = \frac{\sum_1^u TP}{\sum_1^u TP + \sum_1^u FP} \quad (2)$$

$$Recall = \frac{\sum_1^u TP}{\sum_1^u TP + \sum_1^u FN} \quad (3)$$

Typically, a trade-off between these metrics is expected. As the size of forum grows and number of threads increases, *Recall* improves and *Precision* drops. To find out an optimal trade-off between *Recall* and *Precision*, *F1 measure* is introduced by previous studies. This measure combines *Recall* and *Precision* into a single measure and weighs them equally. Equation (4) defines *F-measure*:

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

In order to evaluate our method, we used data from several courses of Coursera. We chose three course forums, namely *Asset Pricing*, *Online Games*, and *Data Science* with 2846, 8,072, and 28,295 valid posts, respectively. As the contribution of learners toward the final weeks of course increases, we decided to use posts from the first 75% time period of each course to train our recommender system. Also, posts of the 25% remaining time allocated to test our system performance. Table III shows each course specifics in the Coursera dataset.

TABLE III
Coursera Courses to Evaluate Proposed System

Course Name	Weeks	Train Days	Test Days	Total Threads	Number of Users
Asset Pricing	9	47	16	673	392
Online Games	6	32	10	784	1355
Data Science	8	42	14	4566	6173

We examined the proposed system performance with different minimum values for *support* measure. Also, minimum *confidence* value set to be 0.1 in experiments. The *Confidence* value of 0.1 is relatively satisfying compared to other studies where confidence value is not mentioned in evaluations [16]. Users categorized in three groups based on their *WOIR* and their community detected under conditions similar to the ones explained in Section IV. Results for different course forums with minimum *support* of 0.005 and

0.0026 are shown in Table IV.

Minimum *support* to evaluate our system is chosen experimentally. Results indicate that by decreasing the *support* threshold, the number of discovered association rules increases consequently. This increase causes recommendations count to expand more rapidly. *Precision* values are almost identical in various *support* thresholds, which means with raise in recommendations number both correct and incorrect recommendations increase. Also, the difference in forum size does not make an impressive change in *precision*. However, lower *support* thresholds result in higher *Recall* and *F-measure* for all three courses. It indicates that more recommendations by altering minimum *support* value lead to more correct recommendations as well as covering more threads interesting for the user.

TABLE IV
HYBRID RECOMMENDER SYSTEM PERFORMANCE

Course Name	Minimum Support	Average Recall	Average Precision	Average F-measure
Asset Pricing	0.005	0.2553	0.4915	0.33605
	0.0026	0.5779	0.5250	0.55018
Online Games	0.005	0.3378	0.5103	0.40651
	0.0026	0.5973	0.5453	0.57012
Data Science	0.005	0.2933	0.5213	0.37539
	0.0026	0.6394	0.5662	0.60058

VI. CONCLUSION AND FUTURE WORK

Q&A forums have become indispensable elements for MOOCs success. Due to the large number of students in an offered course, information overload becomes an inevitable problem for forums. To tackle these problems recommender systems can be helpful to guide learners through various threads available in MOOC forums. This guidance would help learners to address their question properly and also may prevent them from dropping courses. We designed a hybrid recommender system based on social network analysis and association rule mining techniques. The proposed system performs well with minor background information about users profile and posts content compared to other studies. Also, initial results indicate that accuracy of recommendations made by the system is exceedingly acceptable.

In the future, we will continue to take other information provided by the social network into account to make more precise information. For example, we will study users distance from each other in the social network to examine their similarity more elaborately. We will consider not only users posts, but also their visits and spend time on threads to evaluate their contribution. Also, for large datasets with numerous discovered association rules exploring their bipartite graph will be worthwhile to study more.

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