A Novel Recommender System based on Two-level Friendship Ties within Social Learning

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Abstract: Nowadays, social networks are starting to emerge as a huge part of e-learning. Indeed, learners are more attracted to social learning environments that foster collaboration and interaction among learners. To enable learners to handle their time and energy more effectively, recommendation systems tend to address these issues and provide learners with a set of recommendations appropriate to their needs and requirements. To this end, we propose a recommendation system based on the correlation and co-occurrence between the activities performed by the learners on one hand, and on the other hand, based on the community detection based on two-level friendship ties. The idea is to detect communities based on friends and friends of friends, and then generate recommendations for each community detected. We test our approach on a database of 3000 interactions and it turns out that the two-level recommendation system based on friendships reaches a high accuracy and performs better results than the recommendation system based one level friendship ties in terms of precision as well as accuracy. It turns out that expanding the detected communities to generate new communities leads to more relevant and reliable results.

1 INTRODUCTION

In the midst of several difficulties in face-to-face learning, distance learning is a necessity, especially when face-to-face learning is no longer possible (Aboagye et al., 2020). In this case, it is highly preeminent to focus on distance learning and the proper monitoring of online learners. With the emergence of the social networking and social learning mode, learners are increasingly turning to social learning as it promotes collaboration and interaction with other learners (Tartari et al., 2019; Tosun, 2018). Being part of an online social environment is one of the finest options available to a learner. In order to streamline learners' tasks and improve the management of information and content, recommendation systems are among the most optimal solutions as long as they manage the large amount of information a learner is confronted with and the associated time and energy (Rezvanian et al., 2019). All of these elements are counted among the key benefits of recommendation systems, hence their importance within learning environments. In the literature, many recommendation systems have been proposed for distance learning (Panagiotakis et al., 2020 ; Ansari et al., 2016; George, 2019), but not much importance has been dedicated to social learning and social learning networks. Many researchers are limited to considering explicit feedback from learners and their direct evaluations in order to generate recommendations (Salehi, 2013), but implicit feedback should also be included in the recommendation process. On the other hand, there are recommendation systems that can meet the requirements of social networks, but are developed in other contexts besides e-learning. All these points render a recommendation system's work incomplete in the distance learning context, hence the need to re-propose a recommendation system taking into account both implicit feedbacks in particular and considering community detection according to a reliable and relevant criterion since we are dealing with social networks. A learner needs above all a learning atmosphere that encourages interaction and collaboration, and to achieve that, he needs to receive all the support he truly requests, including a relevant recommendation system providing recommendations based on his interactions and implicit feedbacks.

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In our work, we propose a recommender system considering implicit feedbacks, i.e. activities carried out by the learners, and going beyond communities based on one-level friendships to reach two-level friendships. Our recommendation system is therefore based on several points: (1) Integrating learner activities by considering the two notions of correlation and co-occurrence, (2) Detecting communities based on friendships and then broadening the scope of communities to include friends of friends, and (3) generating recommendations for each detected community.

The article is divided into several parts. The second part outlines a general overview of community detection and recommendation systems based on community detection. The third part deals with the recommendation approach proposed in details. The fourth part concerns the tests performed and the results obtained. The final part summarizes the article in general and the next directions to pursue.

2 BACKGROUND

2.1 Community Detection Algorithms

In order to analyse the structure of the relationships between entities, regardless of the nature of these entities, they are generally visualized by graphs. In e-learning, for example, it is possible to model the relationships and interactions between different learners. Learners are modelled by vertices and interactions are presented in the shape of edges. A graph is therefore made up of several communities, and a community is made up of vertices strongly linked to each other than to the other vertices of the graph. We can decide on the type of graph based on several criteria (Beauguitte, 2010):

- The orientation of the graph: There are two types of graph concerning the orientation, oriented graph or non-oriented graph. The direction of the links judges the orientation of a graph. The symmetry of the corresponding adjacent matrix most often depends on the nature of the graph; whether it is oriented or not.
- The type of links existing between nodes: It is possible to distinguish several types of graphs based on the nature of the links; binary graphs whose links express the presence of interaction or relationship between two nodes, and non-binary graphs whose links not only reveal the presence of a relationship, but also its intensity.
- The number of sets of vertices: If the graph consists of a single set of vertices, we would call it a unipartite graph. If the graph contains two different sets of vertices and each set belongs to a specific category, we talk about a bipartite graph.

To detect communities, many algorithms are available. Among those we will explore in our work, there are four:

- Louvain (Blondel et al., 2008): The Louvain algorithm is based on several phases. First of all, each node is considered as an individual community. Then, each node is associated with its closest neighbours and the gain in modularity is calculated (Equation 1), then it is inserted into the community which provides the maximum value of modularity. Finally, the process is performed several times until the modularity gain converges.

$$\Delta Q = \left(\frac{\sum_{in} + b_{i,in}}{2p} - \left(\frac{\sum_{tot} + b_i}{2p}\right)^2\right) - \left(\frac{\sum_{in}}{2p} - \left(\frac{\sum_{tot}}{2p}\right)^2 - \left(\frac{b_i}{2p}\right)^2\right)$$

Equation 1. Modularity gain in Louvain

S_{ij} is the weight of the edge between nodes i and j

- InfoMap (Rosvall et al., 2009): This algorithm is based on an equation called the map equation (Equation 2). The principle is straightforward, just minimizing the random walk within the graph. In other words, if a random walk keeps the same connections, it is due to the fact that the vertices linked to these connections are part of the same community.

$$Map\ equation = w \curvearrowright) \log(w \curvearrowright) - 2\sum_{j=1}^{J} \curvearrowright \log(w_j \curvearrowright) - \sum_{k=1}^{K} w_k \log(w_k) + \sum_{j=1}^{J} (w_j \curvearrowright + w_j) \log(w_j \curvearrowright + w_j)$$

Equation 2. The map equation

M: Network with K objects $(k = 1,, K)$ et J groups $(j = 1,, J)$
w_k: The weight of all connections of i.
w_j: The sum of the weights of all connections of the objects belonging to k.
$w_k \curvearrowright$: The sum of the weights of all the connections of the objects of k leaving the group.
$w \curvearrowright$: The sum of the weights of all the connections of the objects belonging to

- Walktrap (Pons & Latapy, 2005): Walktrap is part of the family of algorithms based on random walks. The concept is to minimize random walks within the same community and maximize them between communities. Like Louvain, the algorithm starts by considering each node as an individual community. Then, the distance between one community and another is computed (Equation 3), and merging the communities having the minimal distance between them, the process is repeated until the algorithm converges.

$$\Delta\sigma\,(C_1, C_2) = \frac{1}{n}\left(\sum_{j\in C_3} {r_{jC_3}}^2 - \sum_{j\in C_1} {r_{jC_1}}^2 - \sum_{j\in C_2} {r_{jC_2}}^2 \right)$$

Equation 3. Random walk variation

- Edge Betweenness (Cuzzocrea et al., 2012): This is another measure of the centrality of a vertex in a graph. The centrality of a vertex is expressed as follows (Equation 4):

$$g(p) = \sum_{v_j\in V} \sum_{v_k\in V} \frac{\sigma_{v_j v_k}(p)}{\sigma_{v_j v_k}}$$

Equation 4. Edge centrality

$S =< V, P >$: Non oriented connected graph.
v_j, v_k: Two nodes in S.
p: An edge part of V.
$\sigma_{v_j v_k}(p)$: The number of shortest paths between v_j *and* v_k.

2.2 Related Studies

Gasparetti et al. provide a review of the general literature on social recommendation systems based on community detection (Gasparetti et al., 2020). The main objective is to clarify research directions regarding community detection and its relation to recommendation systems. A recommender system based on community detection therefore requires several steps:

- Data collection.
- Content extraction and tie recognition.
- The reduction of dimensionality.
- Detection of communities.
- Recommendations.

It is worth mentioning from this work that recommender systems based on the community detection still require efforts and new avenues to generate more relevant recommendations. Boussaadi et al. focus on recommendation systems based on supervised learning in a purely academic learning context (Boussaadi et al., 2020). Indeed, the approach focuses on two main steps. The first step is to group researchers who are likely to be engaged in the same topic. Then, communities are detected in each cluster identified beforehand. The purpose is to reduce the time in terms of generating recommendations and provide more prominent results. The results highlight the importance of integrating community detection to generate articles for researchers. As several works performed, Parimi and Caragea aim at combining community detection with the adsorption algorithm to generate recommendations in the form of articles (Parimi & Caragea, 2014). The preferences of the considered users are rather implicit. Integrating the detection of communities as a preliminary step facilitates the task for the adsorption algorithm and detects the closest neighboring users. The test was performed on two datasets: at DBLP level and at Book Crossing level. It turns out that the community detection improves the performance of the adsorption algorithm. Several recommendation systems are based solely on traditional collaborative filtering techniques. Cao et al. propose an improved version of collaborative filtering; a version that integrates community detection as well. In a first step, the evaluation matrix leads to the similarities obtaining the network (Cao et al., 2015). Then, communities are detected based on the network and an optimization algorithm. Finally, recommendations are generated for each community. Lalwani et al. propose in this paper is to integrate the detection of communities (Lalwani et al., 2015). Communities are detected through social interactions between users. The system goes through several steps:

- Detect communities based on the friendships between users.
- Generate recommendations in each community using collaborative filtering.

The experiments were carried out based on MovieLens and Facebook data, and involve social interactions in the shape of friendships between users.

3 THE PROPOSED APPROACH

In this section, we propose another vision of recommendation systems based on social interactions through friendships; a vision based not exclusively on friends, but also on friends of friends. That is, instead of applying a unique level of friendship, we add another level of friendship considering friends and friends of friends. This will broaden the size of communities and the scope of recommendation systems. The concept is straightforward, just add one more step to the previous recommendation system based on social interactions. This says that from the communities detected by social interactions, we identify the friends of members of the same community and then we integrate these new members with the old members of the same community. In this way, the community is enlarged and the calculation of recommendations might be more relevant. We can summarize the general process in the following steps:

- Identify social interactions between individuals through friendship ties.
- Detecting communities based on social interactions through friendship ties.
- Identify friends of individuals who are members of the same community.
- Identify new communities based on social interactions across two levels (friends and friends of friends).
- Calculate recommendation scores for each new community identified.
- Generate recommendations for each new community identified.

3.1 First Phase

The first phase consists in detecting communities based on friendship ties existing between the different learners. We are going to test several algorithms to opt for the optimal one: Louvain, InfoMap, Walktrap and Edge Betweenness.

3.2 Second Phase

After detecting communities based on friendship links, the next step is to identify the friends of members who are part of the same community, and thus obtain new communities including friends and friends of friends as shown in figure 1.

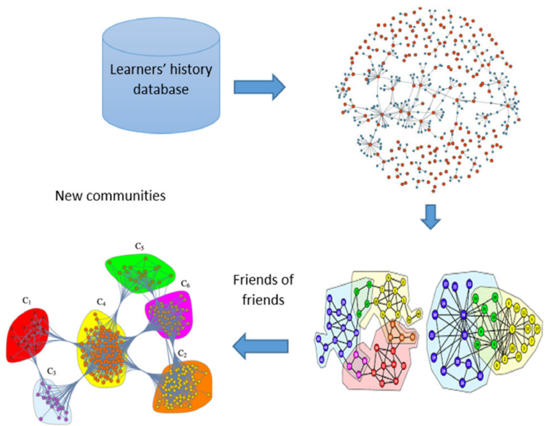

Figure 1: Schematic synthesis of the two-level friendship links process in the recommendation system.

3.3 Third Phase

When new communities have been detected, and which hold more members than the original communities, we reach the main step of calculating recommendations. Our calculation approach consists in defining the correlation and co-occurrence existing between the different activities performed by the learners. In our previous work, we have already developed the part of the calculation of recommendations based on correlation and co-occurrence (Souabi et al., 2020; S. Souabi et al., 2020). First of all, we identify the actions performed by the learners that are associated with the recommendations (primary action directly associated with the recommendations and secondary actions in the second). The idea is to calculate the correlation scores (Equation 7) from the correlation matrix (Equation 5) and the co-occurrence scores (Equation 6) from the co-occurrence matrix, and finally generate the total scores from the two previous scores. All these operations are performed for each community individually.

$\{f_1, f_2, \dots, f_n\}$: Learning objects to recommend.

$\{c_1, c_2, \dots, c_m\}$: The activities performed by the learners such as a_1 is the primary activity and $\{a_2, \dots, a_m\}$ are secondary activities.

$\{(r_{f_1c_1}, \dots, r_{f_1c_m}), \dots, (r_{f_nc_1}, \dots, r_{f_nc_m})\}$: History of activities performed by learners regarding each learning object.

$\{(R_{f_1c_1}, \dots, R_{f_1c_m}), \dots, (R_{f_nc_1}, \dots, R_{f_nc_m})\}$: Co-occurrence history of the activities performed by the learners regarding each learning object.

$$\textit{\textbf{Correlation score matrix}} = \begin{bmatrix} r_{f_1c_1} & r_{f_1c_2} \cdots & r_{f_1c_m} \\ r_{f_2c_1} & r_{f_2c_2} \cdots & r_{f_2c_m} \\ \vdots & \vdots & \vdots \end{bmatrix} \times [1 \quad cor(c_1, c_2) \quad \dots \quad cor(c_1, c_m)] = [correlation\ score\ (f_1) \quad \dots \quad correlation\ score\ (f_n)]$$

Equation 5. The correlation matrix score

$$\textit{\textbf{Co-occurrence score matrix}} = \begin{bmatrix} R_{f_1c_1} & R_{f_1c_2} \cdots & R_{f_1c_m} \\ R_{f_2c_1} & R_{f_2c_2} \cdots & R_{f_2c_m} \\ \vdots & \vdots & \vdots \end{bmatrix} \times [1 \quad co-occ(c_1, c_2) \quad \dots \quad co-occ(c_1, c_m)] = [co-occ\ score\ (f_1) \quad .. \quad co-occ\ score\ (f_n)]$$

Equation 6. The co-occurrence matrix score

$$\textit{\textbf{Total score matrix}} = co-occurrence\ score\ matrix + correlation\ score\ matrix = [co-occ\ score\ (f_1) \quad \dots \quad co-occ\ score\ (f_n)] + [correlation\ score\ (f_1) \quad \dots \quad correlation\ score\ (f_n)]$$

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Equation 7. The total scores of recommendation

After having detected the new communities, it remains to calculate the recommendations for each new community detected.

4 TESTS AND RESULTS

A Under the proposed approach, we suggest considering two levels of social interactions so that more relevant and precise recommendations can be generated. Therefore, in addition to adding a preliminary step of community detection, we propose to integrate social interactions with two levels, i.e., integrating friends and friends of friends in the same community.

The database we will focus on in our experiment is a dataset extracted from a video-based educational experience using a social and collaborative platform.[1] The interdisciplinary learning activity is carried out between students in computer engineering and media and communication. The collaborative social network is divided into groups, each group including students in computer engineering and media and communication. We opted for this database because it perfectly matches our context and expectations, and it supports all the activities carried out by the learners within the social network while providing them with several supports, such as: documents, videos, presentations. Students have a workspace where they can share files, images and various resources, as well as messages to interact with other students. The exchange therefore consists of sharing several types of educational material. The database holds 3000 learner interactions containing their activities within the learning network (Martín et al., 2015).

To highlight the performance of this recommendation system and the importance of merging two-tier friendship with recommendation generation, we compare the performance of the one-tier social interaction-based system with the two-tier social interaction-based recommendation system.

4.1 Community Detection

After testing the four algorithms: Louvain, InfoMap, Walktrap and Edge Betweenness, we realize that the most optimal algorithm in terms of modularity and execution time is the Louvain algorithm with the following results (Table 1). We also showcase the communities obtained by the Louvain algorithm in Figure 2.

Table 1: Modularity and execution time according to the chosen algorithm.

Algorithm	Modularity	Execution time	Number of communities
Louvain	0,64	0,03 s	9
InfoMap	0,17	0,03 s	32
Walktrap	0,62	0,03 s	11
Edge Betweenness	0,63	0,03 s	11

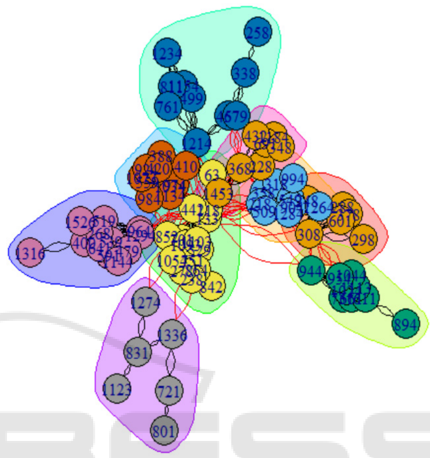

Figure 2: Communities obtained in Louvain algorithm.

4.2 Friends of Friends

This step consists in detecting the friends of the members of each community in order to acquire the following new communities (Table 2).

Table 2: Communities detected by Louvain algorithms and new communities generated by the approach proposed.

Community	Number of members' original communities	Number of members' new communities
Community 1	6 learners	12 learners
Community 2	9 learners	16 learners
Community 3	9 learners	11 learners
Community 4	15 learners	32 learners
Community 5	10 learners	14 learners
Community 6	10 learners	15 learners
Community 7	12 learners	18 learners
Community 8	6 learners	8 learners
Community 9	7 learners	18 learners

[1] http://dx.doi.org/10.13140/RG.2.1.2316.7521

By shifting from one-level to two-level social interactions, the number of individuals increases tremendously and can reach twice the initial number. This implies that the initial size of each community will be multiplied by twice, and therefore more data to process and more data to consider in generating recommendations.

4.3 Evaluating Recommendations Results

To properly evaluate our proposal, we compare the results of the recommendation system based on one-level social interactions with the results of the recommendation system based on two-level social interactions. The evaluation measures included are: accuracy and precision. To evaluate the recommendation system, we made a distribution of the database according to the 20/80 law, which means that we dedicate 80% to create the recommendation model and 20% to test the recommendation model and compare the actual preferences to the predicted recommendations. After detecting the communities, we apply the 20/80 rule for each community.

Many activities have been recorded in this database. We restricted our analysis to those relevant actions according to recommendations generated. Indeed, the video is a very practical support to illustrate certain notions. It is one of the soundest learning techniques as it is supported by images and sound, and these two elements fully attract the learner's attention.

Since the correlation between the primary activity is associated with the recommendations and the other secondary activities, as well as the co-occurrence, the primary activity must be identified in addition to the secondary activities whose relevance comes after:

- The primary activity: Learner evaluation of videos (fivestar).
- The secondary activity: Creating a comment for a video.

- **Precision:**

To measure the relevance of the recommendation system based on two-level social interactions, we resort to precision in the first instance (Equation 8). Considering the same previous communities, the measures are represented in the following table with RSSI1 is the recommendation system based on two-level friendship ties and RSSI2 is the recommendation system based on one level friendship ties (Table 3).

$$Precision = \frac{TP}{TP + FP}$$

Equation 8. Precision of recommender system

Where:
TP: Number of preferred items that are recommended.
FP: Number of preferred items that are not recommended.

Table 3: Precision obtained for RS1 and RS2.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Precision of RSSI1	1	1	1	1	1	1	1	1	1
Precision of RSSI2	1	1	0	0	1	0	1	1	1

We thus visualize the box plot to view the accuracy of the two types of recommendations (RSSI1 and RSSI2) in figure 3. We note that the precision of RSSI1 significantly exceeds the precision of RSSI2 since it reaches a value of 1 for all communities versus values that vary between 0 and 1 for the second recommendation system based on one-level friendship ties (Figure 3).

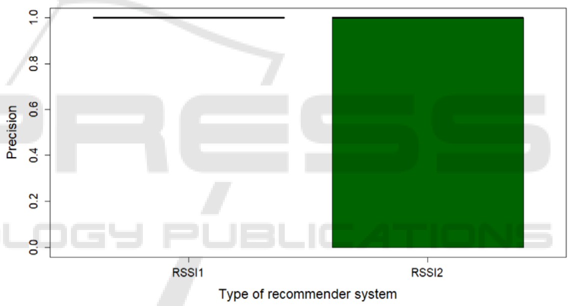

Figure 3: Box plot presenting the variation of precision according to the type of recommender system.

- **Accuracy :**

Secondly, with a view to assessing the relevance of the recommendation system, we measure the accuracy of the two recommendation systems (RSSI1 and RSSI2) for the same communities in Table 4 by using the equation 9:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Equation 9. Accuracy measure in the recommender system

Where:
TP: Number of preferred items that are recommended.
FP: Number of preferred items that are not recommended.
TN: Number of non-preferred items that are not recommended.

FN: Number of non-preferred items that are recommended.

Table 4: Accuracy according to RS1 and RS2.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Accuracy of RSSI1	1	1	1	1	1	1	1	1	1
Accuracy of RSSI2	0,92	1	0,88	0,9	1	0,91	1	1	1

The box plot, reporting the variation in accuracy for the two recommendation systems (RSSI1 and RSSI2), shows the stability of the first recommendation system, as well as its accuracy. The value remains within 1 (Figure 4). As for the second recommendation system based one level friendship ties, one quarter of the values are between 0.88 and 0.91, while three quarters of the data are between 0.88 and 1.

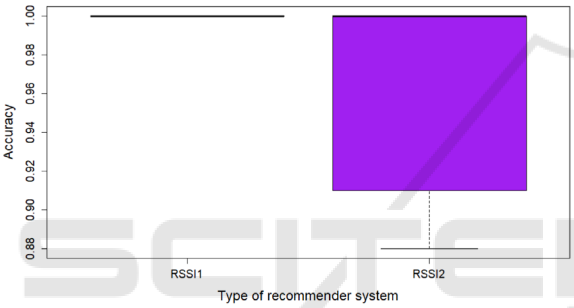

Figure 4: Box plot emphasizing the variation of accuracy according to the type of recommender system.

4.4 Discussion

Based on the findings, the recommendation system based on two-level social interactions seems to produce more appealing results than the recommendation based on one-level friendship ties, whether in terms of precision, or accuracy (Table 5). An average precision of 1 is registered for the recommender approach based on two-level friendship ties against only 0.66 for the recommender approach based on one-level friendship ties. This is due to the recognition of the two-level friendship relations instead of generating recommendations based on one level friendship interactions. Adding an additional level to the level of social interactions leads to more meaningful and relevant results. We obtain a precision and accuracy that reaches a value of 1, which reveals the great added value of social interactions in two levels. The larger the number of friends, the more relevant the generated recommendations are, and the larger the number of data is counted as well. If the number of friends is restricted, the data remains limited and the recommendations may lose their relevance and reliability. It is therefore important to consider social interactions within recommendation systems, but attention must be devoted to the number of friends to be counted within each community.

Table 5: Average precision and accuracy obtained according to the type of recommender system.

Recommender system	Average precision	Average accuracy
RSSI1	1	1
RSSI2	0,66	0,956

5 CONCLUSION

This work addresses a very prominent topic in e-learning: Recommender systems in social learning. Our proposal consists of several core components: (1) Detecting communities based on friendships, (2) Identifying the friends of all members belonging to each community and then building new communities composed of members and friends of members, and (3) generating recommendations for each new community individually based on the correlation and co-occurrence of events performed by learners. This process is developed and requires the use of community detection and matrix computation algorithms. After testing the approach on a database of several learners, it turns out that the recommendation system based on two-level friendship links is more efficient than the one based one level friendship links in terms of precision and accuracy. We thus contributed by proposing a hybrid recommendation system based on two-level friendship links within social learning, which is perceived as a major strength, mainly because community detection is not properly addressed at the social learning level and social learning is not adequately addressed in general. In upcoming research, we intend to:

- Test our approach on a database within our university with the intention of highlighting the importance of community detection in the management of recommendations.
- Dig deeper into the discipline of community detection in online learning; which means to address new aspects of community detection in terms of recommendations not only on social links, but also on other indicators.

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