A Framework for Recommending Learning Peers to Support Collaborative Learning on Social Networks

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Abstract — With advances in social network sites and easy access to Internet services, many learners rely on suggestions from other people on the Internet for easy access to very essential information concerning learning materials, and also to collaborate with each other in order to exchange ideas. Current recommender systems for learning focus mainly on recommending a sequence of learning materials based on learners similarities or similarities between the new learning objects and the ones the user is already familiar with in the past. Many learners prefer collaborative learning than learning on their own or in the classroom, but the major difficulty in engaging in an online collaborative learning is how to get suitable collaborating partners (learning peers). This paper proposes a framework for building a recommendation system that can search social network sites to find and recommend learning peers to the user based on their post, comment, and common friends on the social network.

Keywords — Recommender Systems (RSs); Similarity metrics; Aggregation Function; Probabilistic Model; Bayesian Classifier; and Recommendation Techniques.

I. INTRODUCTION

Social networks bring people together to strengthen collaboration between them. It is now evident that people on the social network connect to friends they already know even without social media, and more interesting, they connect with other people they discover only through the social network [1]. There are many social network sites, but Facebook , Twitter , Myspace , LinkedIn , along with others, are among the most widespread used by many people in different places of the world to have a conversation with the people they already know offline [2]. There are hundreds of thousands of people using those services every day. For instances, according to the recent social networks’ statistics [3], [4], there are over 1.3 billion, 646 million, 200 million, and 30 million registered users for Facebook, Twitter, LinkedIn, and Myspace respectively. They contain a very large amount of data (in gigabyte) that can be used to predict who is a friend of who [5]. This rapid growth of social network sites makes it more challenging to discover both the known and interestingly the unknown people to connect with for efficient communication between one another. Social networks collect very vital information about users to form a large scalable interconnection of a social network, and use such records to recommend people to users depending on the number of friends they have in common. This personalized approach has already been adopted by Facebook (“People you may know”) that suggest people to the users based on the number of their common friends. It was however observed that people are interested in collaborating with more valuable people not yet known to them in addition to keeping in touch with their familiar friends/colleagues [6]. Social networks are one of the most widely used services on the web by both adults and younger people, that if integrated with learning activities it will boost students’ performance.

The concept of social networking can be applied not only to the area of learning, but also to any organizational settings where the social structures are complex. It is difficult in such settings to completely understand the relationship between people (who knows who), and to know how they interact with each other. One way to discover and analyze the relationship between individuals or group of people is through a social network site [7]. Indeed, social network changes the methods of information seeking between people as well as their collaboration behavior [7], [8], [9], [10], [11], [12], [13].

On the other hand, online collaborative learning is a modern discipline within educational science; that unites the idea of group-based learning and the potential of information and communication technology (ICT) to support learning. It becomes a research domain that received much attention from a wide range of disciplines, such as computer science, sociology, education, anthropology, and on and on. [14], [15]. In computer science, computer supported collaborative learning has been studied by many researchers using recommender system. Recommender system is fast becoming a key instrument that plays a significant role in teaching and learning activities, where a common set of learning resources can be shared among users [16]. Many factors such as the level of their skills, their specific interest, and educational background can provide exceptionally appealing information towards proposing a useful, interesting, and comprehensive sequence of learning objects to the user. Most of the studies in recommender systems for learning have only been carried out to either provide sequence of useful items to the user, recommend good learning pathways, find novel learning materials, restrict recommendations to the ones with high credibility, predict usefulness of learning object in a given list of items, or give recommendation of new courses from a university websites [17]. However, for too little attention has been paid to take advantages of the existence of social network sites, this paper proposed a framework for developing a recommender system that can be used by learners to enhance collaborative learning process through social network sites. Three models are proposed in this paper, a probabilistic model that uses
Bayesian classifier to rank the users based on probabilities of matches between them and the active user's profile, aggregation function approach as a model, and a friend-of-friend model to recommend users based on their common connections with the active user.

This paper has been divided into five parts including this introductory section. Section 2 contains related work, section 3 gives the required background of the study, the proposed approaches are presented in section 4, and finally section 5 conclude the paper and suggests important issues for possible future research.

II. RELATED WORK

Over the past decades there has been a dramatic increase in both recommender systems for learning and social network based recommender systems, but it is not so common to find one that talks specifically on recommending collaboration partners based large number of registered users we have on the social network sites, therefore, in this section, we mentioned some of the research work that are related to our study.

As a result of rapid increase in the volume of social network, scanning through the whole network before making recommendation becomes a problem, [18] has therefore proposed combining social information and semantic information into one algorithm to compute sequence of recommendations by visiting only some part of the network. However, for making efficient top-N recommendation, [19] suggests effective methods to improve recommendation accuracy. Our proposed framework resembles [20] where the author proposed a model for trust-based recommendation system on a social network. [21] works on a system called “SmallBlue”, which is a social context-aware platform that searches the social network to finds and recommends experts in a particular work domain to the users for collaboration and sharing of resources concerning their area of expertise. [22] performed a comprehensive user study of the same system to evaluate its efficiency. The study was motivated as a result of an overwhelming number of people (about 1,700) using the system within a short period (6 months) of its implementation. [5] proposed a system that makes friend recommendations on the social network, the system known as “link prediction problem”, works based on an algorithm called “algorithmic small world hypothesis” which traverses all paths of a limited length. The system gave an accurate and precise friend recommendation. An experimental comparison between their proposed technique and the actual link prediction algorithm was carried out using data sets from three different social network sites (Facebook, Epinions, and Hi5). Similarly, [1] is a study of people recommender systems that were designed to assist users in discovering both familiar and unfamiliar friends on social network sites. They used four different algorithms (content matching, content-plus-Link, Friend of Friend, and SONAR algorithm) to implement the recommender engines, and evaluated their performance through a survey of users and a field study of 500 and 3,000 users respectively.

In the area of collaborative learning, efforts have been made by many researchers [23] to take advantage of the web 2.0 to support learning by constructing an intelligent collaborative e-learning systems [24], [25], [26].

III. BACKGROUND OF STUDIES

This research work comprises of three distinct research domains, the social network, collaborative learning, and recommender systems domain. Therefore, this section gives an overview of each area under this section.

A. Social Networks

Recently, researchers in the area of social networks paid considerable attention towards analyzing the structure of social networks. Using the concept of graph theory where each point (nodes) in the graph represent people in the social network and the links/edges between nodes to represent the interactions, collaborations between them can help greatly in understanding the basic concept of social network [27]. Studying graph theory to represent social network properties and the availability of social network datasets [28], [29], [30] provide interesting research opportunities to deeply investigate many hidden properties of social networks. However, links in the social network are dynamic, which means people can decide to connect to other people or remove an existing connection. This dynamic nature and an increase in the number of people participating in the social network make it the largest collaborative environment where most of our daily activities can be operated.

Social network site (SNS) is any website that allows people to create public site and use it to interact with other registered users. According to [2], SNSs are web-based services that enable people to:
1) Build a semi-public or public profile inside a separated system.
2) Come across an inventory of others that are not connected to them directly.
3) Go through the list of all people connected to them and also view the details of all their connections.

Fig.1: Two Types of Connections on Social Networks.

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Social network has a lot of applications in an academic environment for creating relationships between people. Some of those applications include formation of research and learning teams, organization of expert communities, organizing collaborative learning, and so forth.

Fig. 2: Architecture of a Social Network

Furthermore, the nature of connections between people may vary between one social network platform and another. For instance, some connections require mutual agreements between people to be established (two-way connection) like Facebook, while others like Twitter require only the desire of one person to follow any other one (one-way connection). Fig. 1 (a) and (b) are examples of those connections where a one-directional line and a bi-directional (sometimes non-directional) line are used to represent one-way and two-ways connections respectively. Fig. 2 shows the simpler way to explain how people are connected in a social network by visualizing the network as a graph where each point (node) in the graph represents a person and the link between nodes shows whether two or more people are friends to one another. Of course, people can decide to stay with very few number of friends or even to stay alone (like newly registered users) on the social. SNSs such as Facebook have a very high density, and the degree centrality between people is rapidly increasing [31].

B. Recommender Systems

F. Ricci et al [32] defined recommender system as a software tool and techniques to provide suggestions of useful items to the user. The word item is a general term that referred to what the system will recommend to users [33], they can be of different forms such as an online news to read, a music to listen, a learning material for study, or even other users to collaborate with. Those kinds of systems are mainly useful to people who does not have enough experience to make a good choice among potentially many alternatives of items that a website offer [34]. Some of them try to answer an important question of whether a user will be interested in a new item or sequence of items as follows:

1) By checking all sets of items the user likes previously, and try to compute the similarity between them and the new item.
2) By considering the people who like that item and then compute the similarity between them and the current user.

While variety of definitions of the term recommender system have been suggested, the definition suggested by Adomavicius et al [35] can be similarly used to give the basic concept of recommender systems, where he said a recommender system presumes that there is a set Items or just I consisting of all available items and a set Users or just
filtering is the easiest to implement and the most widely used technique that provides recommendations based on users’ or items’ similarities. The similarities are calculated based on previous rating histories of users on some group of items. There are many ways of computing similarities between users or items; they include Pearson correlation coefficient (equation 2&3), cosine measure (equation (4)), etc. TABLE. I presents the summary of the most commonly used metrics and the ranges of possible values they can take. Content-based system uses user profile to recommend items based on the relationship between the attributes of the profile and the attributes of the new item. Demographic-based systems use demographic profile of the user to recommend the most suitable items to the user. Knowledge-based recommender system uses user preferences and the domain knowledge of items to make recommendations. Nevertheless, each of those techniques has its own individual shortcomings, such as sparsity problem, overspecialization, new user problem, new item problem, etcetera, therefore, hybrid-based technique were introduced to combine two or more of the above-mentioned techniques to overcome some of those individual flaws. Yet, despite the limitations of non-hybrid techniques, people prefer to use them due to their simplicity in implementation since the hybrid system will require combining the implementations of two or more non-hybrid techniques.

Now that we know what the system is expected to do, the question now is how the estimation in equation (1) can be achieved by the system? The methodologies or techniques the system used to perform this task are known as the recommendation techniques. Many recommendation techniques are used to generate recommendations to the user, R. Burke [36] classified recommender systems based on five different classes of recommendation techniques. In addition to the three most commonly approaches, namely, content-based, collaborative filtering, and hybrid techniques, [36] also considers demographic and knowledge-based as two other recommendation techniques. Collaborative filtering is the easiest to implement and the most widely used technique that provides recommendations based on users’ or items’ similarities. The similarities are calculated based on previous rating histories of users on some group of items. There are many ways of computing similarities between users or items; they include Pearson correlation coefficient (equation 2&3), cosine measure (equation (4)), etc. TABLE. I presents the summary of the most commonly used metrics and the ranges of possible values they can take. Content-based system uses user profile to recommend items based on the relationship between the attributes of the profile and the attributes of the new item. Demographic-based systems use demographic profile of the user to recommend the most suitable items to the user. Knowledge-based recommender system uses user preferences and the domain knowledge of items to make recommendations. Nevertheless, each of those techniques has its own individual shortcomings, such as sparsity problem, overspecialization, new user problem, new item problem, etcetera, therefore, hybrid-based technique were introduced to combine two or more of the above-mentioned techniques to overcome some of those individual flaws. Yet, despite the limitations of non-hybrid techniques, people prefer to use them due to their simplicity in implementation since the hybrid system will require combining the implementations of two or more non-hybrid techniques.

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**TABLE. I: SIMILARITY METRICS**

<table>
<thead>
<tr>
<th>S/N</th>
<th>Metrics</th>
<th>Brief Descriptions</th>
<th>Return values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Pearson correlation coefficient</td>
<td>Measures the likelihood of two users to move together. That is when one increases</td>
<td>from -1 to 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>his preferences, then also the other and vice versa</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Euclidean distance</td>
<td>It measures the distance between two people. Takes users as points in Euclidean</td>
<td>from 0 to 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>space, find the distance of d and returns the inverse of 1+d</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Cosine measure</td>
<td>Measures the angle between two users and return the cosine of that angle</td>
<td>from -1 to 1</td>
</tr>
<tr>
<td>4</td>
<td>Spearman Correlation</td>
<td>Similar to 1 above with some variant that the result is based on the relative rank</td>
<td>either -1 or 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>of preference value</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Tanimoto coefficient</td>
<td>Is the ratio between the number of common items rated by two users and the</td>
<td>from 0 to 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>collection of all items they rated</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Log-likelihood test</td>
<td>Does not take preferences of an individual user into account. It is similar to 5,</td>
<td>from 0 to 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>only that it measures how unlikely it is for two users to rate common items</td>
<td></td>
</tr>
</tbody>
</table>

However, in some cases, the utility function \( \varphi(u, a) \) requires additional information (context) to make recommendations [37]. Those contextual information may include time of the day, day of the week, for instance, recommending a restaurant to go on weekends may be different from that of working days, or buying cloth during winter season may be different from that in the summer, and so on.

\[
\begin{align*}
\text{sim}(a, b) & = \frac{\sum_{a \in A_u} v(a, b) (r_{u,a} - \bar{r}_u) (r_{u,b} - \bar{r}_u)}{\sqrt{\sum_{a \in A_u} v(a, b)^2 \sum_{a \in A_u} v(a, b)^2}} \\
\text{sim}(u, v) & = \frac{\sum_{a \in A_u} v(a, v) (r_{u,a} - \bar{r}_u) (r_{v,a} - \bar{r}_v)}{\sqrt{\sum_{a \in A_u} v(a, v)^2 \sum_{a \in A_u} v(a, v)^2}} 
\end{align*}
\]

Where \( U \) that will receive recommendations of an item(s), then there is a utility function that estimates the degree to which a user will like the item. Therefore, \( \forall u \in Users \) and \( a \in Items \), they defined a function \( \varphi: Users \times Items \rightarrow r \) where \( r \in \mathbb{R}^+ \) within a defined interval. For items \( a \) whose ratings \( r \) by the user \( u \) are not known, the system will estimate \( \varphi(u, a) \) and select the ones with the higher values of \( r \) (maximum of \( \varphi(u, a) \)) and recommend to the user. That is:

\[
\forall u \in Users \ a = \text{arg max } \varphi(u, a) 
\]

Where \( U_{a,b} \) in (2) is the user who rated items \( a \) and \( b \). Also \( A_{u,a} = \{ a \in A| r_{u,a} \neq \emptyset \text{ and } r_{v,a} \neq \emptyset \} \) \( \bar{r}_u \) and \( \bar{r}_v \) are taken over ratings given by \( u \) and \( v \) to a common item \( a \).

While for cosine metric, \( \text{sim}(u, v) \) is obtained using \( \cos(\vec{u}, \vec{v}) \) so that:

\[
\begin{align*}
\cos(\vec{u}, \vec{v}) & = \frac{\vec{u} \cdot \vec{v}}{||\vec{u}||_2 \times ||\vec{v}||_2} \\
& = \frac{\sum_{a \in A_u} v(a, a) r_{u,a} r_{v,a}}{\sqrt{\sum_{a \in A_u} v(a, a)^2 \sum_{a \in A_u} v(a, a)^2}} 
\end{align*}
\]

Where \( \vec{u} \) is a dot product between vectors \( \vec{u} \) and \( \vec{v} \).

Recommender system is a new research area that in recent times continues to receive so many attentions from
both academic and commercial settings. Nowadays, some of the major academic journals such as [38], [39], [40], [41], and many more, dedicated a special issue for research and development in this new area. Furthermore, there are several conferences and workshops like [42] taking place annually purposely to present new findings in recommender systems. In terms of teaching and learning recommender systems, many universities and colleges around the world have introduced this course at both graduate and undergraduate level. More so, it plays very vital role in many online businesses like Netflix.com, Amazon.com, Tripadvisor.com, and so on. In fact, Netflix.com promise to give a prize of a million dollars to any team or an individual who succeeded in improving the performance of their recommender system [43]. This shows that not only users are the beneficiaries of the system but also the service providers as it helps in increasing the number of sales, getting a better understanding of customers’ behavior, selling more diverse items, and many other advantages [32].

C. Collaborative Learning

Collaborative learning is a method by which two or more people learn or prefer to study something together to exploit the skills, knowledge, resources, and ideas of one another. It helps learners to gain knowledge through collaboration and sharing of ideas between them or between groups of people [44]. In other words, collaborative learning can be seen as a procedure in which learners undertake a common task where each person is accountable and depends on another person. It is based on the idea that knowledge can be innovated in a population where people interact actively by sharing their experiences on a particular topic of discussion. The process can be either by face-to-face discussion, group discussion, online forum, and the like. Sequel to the adage that says "two heads are better than one”, researchers confirmed that working in a group is an important way of learning [45]. New technologies and the existence of the second generation world-wide-web (web 2.0) that focused on how can people collaborate and share information online have now interfaced with the traditional classroom teaching [46].

IV. PROPOSED APPROACHES

The methodological approach taken in this research is a mixed methodology based on content-based filtering technique, Bayesian classifier, aggregation function, and a friend of friend algorithm. The process of recommending learning peers begins at a Post/Comment Analyzer component of the system in Figure. 3 by using an information retrieval technique [47] where people on SNSs will be retrieved based on their posts or comments. That information will be processed to form a vector $V_{pk}$ for each person $pk$ (where $k = 1, 2, ..., m$) containing his corresponding post or comment, and send the result to the Extracted Users component in a structured form. Similarity Checker will receive the collection of those users’ vectors and the active user’s (learner) profile to filter the people to be recommended for collaboration. Three models are proposed in this paper, a probabilistic model that uses Bayesian classifier to rank the users based on probabilities of matches between them and the active user’s profile, aggregation function approach, a friend-of-friend approach to recommend users based on their common connections with the active user.

A. Probabilistic Modeling

Many research disciplines in science and engineering deal with problems of the structure: tell me more about an object $O$ given that I have knowledge of some data $F$ and how it is generated [48]. This scenario can be modeled using probabilistic modeling as follows:

$$
p(O/F) = \frac{p(F/O) \cdot p(O)}{p(F)}
$$

then we are now interested in the equation below:

$$
p(O/F) = \frac{p(F/O) \cdot p(O)}{p(F)}
$$

This shows how we can generate the knowledge about the new object (posterior probability $p(O/F)$) using our knowledge of the data $F$. This relation is called Bayes' theorem, which can be used to model many real life problems.
**A1. Using Bayesian Classifier**

Bayesian classifier as an inductive learning approach is proposed to learn the users profile for a good recommendation. Let $\omega_1, \omega_2, \ldots, \omega_n$ represent $n$ number of keywords in the user profile that can be used to find the relevant people for collaboration. Then we want to compute the probability $p(V_k / \omega_1, \omega_2, \ldots, \omega_n)$ to know the similarity between the learner and the person $p_k$, for all $k$.

$$p(V_k / \omega_1, \omega_2, \ldots, \omega_n) \propto p(\omega_1, \omega_2, \ldots, \omega_n / V_k) p(V_k)$$

In particular, we propose to use Naïve Bayes Classifier as it is proving to outperform other classifiers in making good recommendation [49] to estimate $p(\omega_1, \omega_2, \ldots, \omega_n / V_k) p(V_k)$. It is the appropriate machine learning algorithm to use due to its ability to add prior knowledge, good prediction time, and to prevent that presence or absence of one of those words $\omega_i$ in $V_k$ will not affect the other. Therefore, $p(\omega_1, \omega_2, \ldots, \omega_n / V_k) = p(\omega_1 / V_k) p(\omega_2 / V_k) \ldots p(\omega_n / V_k)$. Among the two commonly used working models (Multivariate and Multinomial) of Naïve Bayes classifier, we choose multinomial to count how many times $\omega_i$ appeared in $V_k \forall i \leq n$ using equation 6.

$$p(\omega_i / V_k) = p(\omega_i) \prod_{t_r \in V_k} p(t_r / \omega_i) N(V_k, t_r) \tag{6}$$

here $t_r$ are the tokens/words in $V_k$ and $N(V_k, t_r)$ is the number of times $r^{th}$ token appeared in $V_k$ for $r=1, 2, \ldots, a$. Recommended people will be sorted based on the probability obtained from their respective vectors.
B. Using Aggregation Function

Aggregation functions or just aggregation means a technique of combining keywords or numerical values $\lambda_1, \lambda_2, \ldots, \lambda_n$ to give single value $V^n(\lambda_1, \lambda_2, \ldots, \lambda_n)$, for which the outcome of the aggregation depends on each individual value [50]. They are used in several research disciplines, like finance, computer science, and statistics [51]. In recommender system, aggregation function referred to a function where several criteria, preferences, or features are gathered together to produce a particular value (rating) that can be used to make an appropriate recommendation. This technique has been used at different levels for many reasons in recommender systems [52].

However, due to the high peoples’ demand in electronic objects and information from vast databases, recommender systems are receiving extra recognitions for their ability to find and recommend the most suitable item to the user, which may be difficult/time-consuming if not impossible to locate manually among the array of items in those large databases. Those items may include news articles [53], medical treatments [54] [55], web-pages [56], music [57] [58], movies [59], people [60], toursisms [61] [62], and other products [63] [64]. Increase in the number of items in the databases may make it difficult to quickly and accurately recommend good items to the users. Therefore, introducing aggregation function into the domain of recommender systems helps in increasing the system’s performance and accuracy by making sure that only relevant items that can satisfy the users’ preferences will be recommended [52].

There are some common aggregation functions such as maximum(), minimum(), median(), mode(), arithmeticMean(), sum(), and others that are commonly used in various computer science fields (e.g. programming, relational algebra, electronic spreadsheet, databases, and so on.). Three of them (minimum, maximum, and Arithmetic mean) are usually applied in the field of recommender system for recommending most useful items to the users. Furthermore, as mentioned in [52], aggregation functions can play a vital role in any type of recommendation systems. For instance, in collaborative filtering recommenders, it can be used in aggregation of user preferences, aggregation of item/user features in content-based filtering, and in obtaining an overall score given some recommendation scores from different recommendation techniques in a hybrid-based system.

However, since we are dealing with profile of active users and the features of the social network users to find the appropriate learning peers, therefore, we choose to follow the content-based aggregation of features described in [52]. An aggregation function is defined $\forall n > 1$ as:

$$\Phi: [0,1]^n \rightarrow [0,1]$$

A function $\Phi$ has some interesting properties as stated in [51] that:

1. $\Phi(0,0,0,...,0) = 0$ and $\Phi(1,1,1,...,1) = 1$ 
2. Monotonicity: where $\forall i, j = 1, 2, 3, \ldots, n$

$$\lambda_i \leq \lambda_j \Rightarrow \Phi(\lambda_i) \leq \Phi(\lambda_j) \quad \forall \lambda_i, \lambda_j \in [0,1]^n$$

Those properties make it possible to employ aggregation function into the recommendation of learning peers in a social network since the arguments in the function can stand as some keywords ($\omega_1, \omega_2, \ldots, \omega_n$) obtained from the user profile and those in the vectors ($V_{pk}$) of the extracted users.

B1. Aggregating User Features

As we mentioned in section 1) when using the Bayesian method, an active user profile is represented as a vector of n keywords ($\omega_1, \omega_2, \ldots, \omega_n$), and the vector $V_{pk}$ of an extracted user $p_k$ will be considered for recommendation based on the level at which they satisfy those keywords in the active user’s profile. Therefore, the relationship between each $V_{pk}$ and the user profile can be described using some values $x_1, x_2, \ldots, x_n$ which determine whether a keyword $\omega_i$ matches with some token $t_r \in V_{pk}$. That is, $x_i = 1$ if $\exists t_r \in V_{pk}$ such that $\omega_i = t_r$, otherwise $x_i = 0$. Fig. 4 also explains the steps to form the aggregation function $\Phi(x_1, x_2, \ldots, x_n)$. The overall rating $R(u, V_{pk})$ between the active user $u$ and the person $p_k$ is then determined by aggregating $x_i$.

$$R(u, V_{pk}) = \Phi(x_1, x_2, \ldots, x_n) \quad (7)$$

The value $R(u, V_{pk})$ in the above equation will be used to rank the extracted users for recommendation. However, the two properties of aggregation function stated earlier (the boundary and monotonicity conditions) must be observed for any function to be an aggregation function. Also going back to where we classified aggregation functions as either minimum, maximum, and Arithmetic mean, they can be further classified as Disjunctive, Averaging, Conjunctive, or Mixed depending on their general performance towards given inputs [65] [66] [67] as follows:

- Conjunctive: if $\Phi(t) \leq \text{minimum}(x)$
- Disjunctive: if $\Phi(t) \geq \text{maximum}(x)$
- Averaging: if $\text{minimum}(x) \leq \Phi(t) \leq \text{maximum}(x)$
- Mixed: otherwise.

Therefore, in the view of the fact that the model is based on an optimistic reasoning technique in which obtaining some of the features of the active user profile by any relevant vector $V_{pk}$ is enough to conclude that $p_k$ has some features relevant that of the active user’s profile, then disjunctive, OR-like aggregation will be the right process of recommendations [68].
What we want is that higher scores in $\varphi(x_1, x_2, \ldots, x_n)$ to reinforce each other to give a reasonable value to $\mathcal{R}(u, V_p)$ more than any individual $x_i$ will do. This characteristic is called “noble reinforcement”. [68] explains how to use disjunctive aggregation operators for noble reinforcement, and [69], [70] gave details explanations of the operators.

C. Friend-of-Friend Recommendation

Finally, all the approaches we presented above uses content similarities algorithms, which were proved to be more efficient in finding new people on the social network [1]. There are also other possibilities of recommending people based on their common connections. A friend of a friend recommendation can be included the same ways as in [1] where for any two people A and B, and the current user u, if for a function $\varphi$: $\varphi(A, B)$ means A and B are friends, then the system will recommend A to u if $\varphi(u, B)$ is true and u and A where previously not connected. This type of algorithm has been adopted by some social network sites such as Facebook “People you may know” to recommend people to the user based on the degree of their common relationships.

V. CONCLUSION

Recommender system is generally a new research area that attracted attention of many researchers from industrial and academic environments. Although, reasonable achievements have been made so far in this new research discipline, but however, using social network to recommend items to users is still in its infancy stage. Until recently, there were no much works that were specifically for recommending friends/partners for interactions on a social media. Moreover, only little is known about the effect of recommender systems in enhancing collaborative learning, and it is important to know and understand the best techniques to use when building a system that will take the advantage of various social network sites to support learning. Therefore, to enhance collaborative learning for increasing students’ performance, this paper proposed different frameworks for building recommender systems for learning that can recommend learning peers to the user via social network sites. The main purpose of the study was to develop an understanding of the relationship between social network, recommender systems, and the technology-enhanced learning by examining various ways in which social network users can be grouped together to share knowledge and learning resources. We proposed using multinomial Naïve Bayes classifier and Aggregation function to check and recommend people to the user based on their posts and comments. A friend-of-friend algorithm was also proposed to suggest people to the user based on their common friend(s). This study provides an exciting opportunity to people especially those who are new into the area of recommender systems to advance their knowledge of connections between technology enhanced learning and recommender systems. Further research regarding the role of social networks and recommender systems to escalate quality of learning would be worthwhile. We therefore suggested that further study with more focus on other powerful machine algorithms should be carried out.

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