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RESEARCH ARTICLE

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A semantic and social-based collaborative recommendation of friends in social networks

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Summary
The development of social media technologies has greatly enhanced social interactions. The proliferation of social platforms has generated massive amounts of data and a considerable number of persons join these platforms every day. Therefore, one of the current issues is to facilitate the search for the most appropriate friends for a given user. We focus in this article on the recommendation of users in social networks. We propose a novel approach which combines a user-based collaborative filtering (CF) algorithm with semantic and social recommendations. The semantic dimension suggests the close friends based on the calculation of the similarity between the active user and his friends. The social dimension is based on some social-behavior metrics such as friendship and credibility degree. The novelty of our approach concerns the modeling of the credibility of the user, through his/her trust and commitment in the social network. A social recommender system based on this approach is developed and experiments have been conducted using the Yelp social network. The evaluation results demonstrated that the proposed hybrid approach improves the accuracy of the recommendation compared with the user-based CF algorithm and solves the sparsity and cold start problems.

KEYWORDS
collaborative filtering, competency, credibility, friends' recommendation, friendship, hybrid filtering, semantic filtering, social filtering, social recommendation, trust, Yelp social network

1 | INTRODUCTION

Interactions and sharing knowledge over the Social Web in the different forms (chats, online discussions, comments, evaluations, adding items, and so on) have become the main way of communication between people. The study of social-based recommender systems has emerged as users are unable to reach the relevant information due to the exponential growth of social media content. Recommender systems predict the "rating" or "preference" that a user would give to an item. These systems have become increasingly popular and are utilized in a variety of domains including movies, music, research articles, books, products, and so on. Traditional recommender systems typically produce a list of recommendations in one of two methods: collaborative filtering (CF) or content-based filtering (CBF). CF recommenders exploit the user evaluation history and analyse the similarity between user profiles and those of their neighbors. The principle of this algorithm is that users having a great similarity in their profiles have a potential to share the same interest in the future.[1,2] CBF

[Correction added on 20 April 2020, after first online publication: a statement has been added in the acknowledgement section].

recommenders are built on the assumption that users should like items with features similar to those of other items they liked in the past.[3] These systems recommend more items which contain these relevant features to users. They are applied to textual or any other media such as images and videos component items where the system extracts the most important keywords/features that characterized an item, to suggest more items with similar characteristics.

Although the development of traditional approaches is mature, all the recommender systems are based on the assumption that users are independent.[4] However, with the development of social platforms built around the concept of friendship between users, many researchers are now interested in trust-based recommendation systems which combine the trust and social information to improve the accuracy of traditional approaches. According to Sun et al,[4] the performance of traditional recommender systems can be enhanced with the integration of social information, as the friendships among users greatly improve the understanding of user ratings and, therefore, user preferences can be interpreted and inferred more precisely. Moreover, the friendship between users shows that they share similar things.

A review of the literature in this area shows a significant number of works that deal with various issues including personalized recommendation[5-8] and group recommendation.[9,10] Recently, some works have focused on the combination of semantic and social information for the recommendation of items (eg, products, articles, books…), friends (eg, scholar-friends), or services (eg, travels, hotels). We mention the following works: the recommendations-based on semantic analysis of social networks in learning environments,[11] the recommendation of scholar-friends in online academic communities,[12] the social collaborative service recommendation based on users' trust and domain-specific expertise,[13] the friends recommendation in location based social network using multifeatures to partition users.[14] Several areas and topics have attracted the attention of researchers, including the product recommendation in online social networking communities,[15,16] based on the integration of social relationship and product popularity[6] or with opinion mining on purchase,[17] the social-semantic recommender system for advertisements,[18,19] and the semantic association analysis to mine the opinions on online travel agencies.[20]

In this article, we focus on the friends' recommendation in social networks using the CF algorithm based on, both, semantic and social information. Social networks provide an important source of information regarding users and their interactions. CF is a widely exploited technique in recommender systems to provide users with items that well suit their preferences.[21] The basic idea is that a prediction for a given item can be generated by aggregating the ratings of users with similar interest. Rating prediction aims to discover the preferences of users and properties of items based on historical rating information.[22] However, one of the shortcomings of this algorithm is the sparsity and cold start problems due to insufficient rating.[23] Our approach proposes an enhancement of the CF recommendations with semantic and social recommendations. The semantic dimension suggests the semantically close friends based on the calculation of the similarity between the active member and his friends (ie, concerns individuals sharing domains of interest and preferences). The social dimension is based on some social-behavior metrics such as friendship, commitment, and trust degrees between users. The most important contributions of this approach are: (1) the modeling of the implicit user's profile through his/her interactions in the social network; and (2) the modeling of the user's credibility information, which is based on his/her trust and commitment in the social network. The parameters involved in the computation of credibility play an important role in enhancing the recommendation accuracy and effectively tackling the cold start problem.

The remainder of this article is organized as follows. Section 2 gives an overview of related work about social recommendation of friends. Section 3 describes our approach for the recommendation of potential appropriate friends in social networks and presents the proposed hybrid recommendation algorithm. The experimental results and analysis using the Yelp social network are reported in Section 4. Finally, the conclusion is given in Section 5 including some future perspectives.

2 | RELATED WORK

We present in this section the principles of social recommendation and then we will expose some works related to the recommendation of friends (also called members, users, or people) in the context of social networks.

2.1 | Recommendation in social networks

Social networks have been one of the most important topics in the last few years. The state of the art shows that social recommendation has been studied since 1997.[24] This domain has attracted increasing attention with the growing popularity of social media.[25,26] According to Tang et al[27] two main definitions are reported for social recommendation: (1) The first definition considered social recommendation as any recommendation with online social relations such as trust relations, friendships, memberships, or following relations (ie, users are correlated when they establish social relations such as users' preferences which can be influenced by their connected friends); and (2) The second definition considers social recommender systems as any recommender systems that are linked to social media domains[26] and use social media data (eg, social tagging, user interaction). The recommendation in this context concerns any objects in social media domains such as items, tags, people, and communities.

Ma et al[28] highlighted the differences between social-based recommender systems and trust-based recommender systems. According to the authors, social recommender systems use the social friends' network to improve traditional recommender systems. Whereas trust-based recommender systems utilize the users' trust relations and consider that users have similar tastes with other users they trust.

2.2 | Semantic and social based recommendation approaches

The review of the literature about social recommendation shows that much work proposes various approaches to provide personalized recommendations to users. Some works used ontologies and information filtering techniques with social networks to enhance the recommendation process. For instance, Agarwal et al[29] considered a rating matrix based on CF and social relations between users. They have corrected the rating based on users' natural attribute information and characteristics of the interaction intensity between them. Tang et al[30] proposed a topic-based Weibo social networking recommendation model using latent Dirichlet allocation and calculate the interest similarity between users to increase recommendation accuracy. Based on existing Weibo topologies and content-based hybrid recommendation algorithms, Zhang et al[31] proposed a hybrid recommendation algorithm based on social relations and time-sequenced topics. Li et al[32] proposed a social recommender system for generating personalized product recommendations based on preference similarity, recommendation trust, and social relations. Liu and Lee[33] developed a way to increase recommendation effectiveness by incorporating social network information into CF. Wang and Huang[34] integrated the friendships to generate the recommendations, but they did not distinguish the different friendships between users.[4] Chang and Chu[35] proposed a recommendation approach which calculates similarity among users and users' trustability and information collected from the social networks. Banati et al[36] explored the role of explicit social relationship by presenting two novel similarity metrics. The first metric is based on the social behaviour that measures similarity between two users on the basis of "how similar they are in their social relationship." The second metric integrates the social similarity with the interest similarity between two users. Zhang et al[37] proposed a hybrid recommendation system based on semantic interest community and trusted neighbors. Domain ontology is used to construct the user interest model and the integrated ontology-based semantic similarity algorithm is used to obtain the user ontology set. Users with a high degree of diversity are selected as trusted neighbors to construct a hybrid recommendation model with a combination of accuracy and diversity.

On the other hand, some works about social recommendation introduced additional interesting concepts such as spatial proximity, points of interest and item popularity. For instance, Chen et al[5] developed a social recommendation system based on users' attention and preferences. Lai et al[6] proposed a social recommendation method to predict user preferences, and then recommend relevant products in social networks. This method is based on the integration of interactions (to infer their latent interactions in accordance with the user ratings and corresponding reviews), trust relationships, and product popularity. Zhu et al[38] proposed a semantical pattern and prefrence-aware service mining method to make full use of the semantic information of locations for personalized personnalized point of interest recommendation.

2.3 | Friends recommendation in social networks

As we are interested mainly by research on friends' recommendation, we have selected, as fairly representative, the following related work:

- Cai et al[39] proposed a novel neighbor-based CF algorithm to enable people-to-people recommendation in social networks. The algorithm allows the prediction, for a given user, of other users he/she may like to contact. This is done based on user similarity in terms of both attractiveness and taste.
- Ma et al[40] proposed a user recommendation method in social networks using trust relationship and topic similarity. After the identification of users' communities based on trust propagation, the authors modeled social relationships and

then applied a topic model to extract users' topics from their microblogs. Finally, the recommendations were suggested using topic similarity.

- Guo et al[41] studied how to recommend groups to an individual user and proposed a group recommendation system based on users' trust neighbors and similar neighbors' tastes. Users' similar neighbors are based on tag information using users' photos as well as their favorite photos and the common friend information.
- Chen et al[42] proposed a learning-based recommendation method to suggest informative friends to a given user. Informative friends are friends whose posted updates are liked by the user. They are recommended if the preferences of their shared updates are highly associated with the user's preferences. The authors used learning techniques to analyze user behavior and model the latent preferences of users and shared updates. The learned preferences are enhanced by the integration of the learning model with social influence.
- Guo et al[43] proposed a framework to discover the social relationship strength on Instagram for friend recommendation. According to the authors, different actions (eg, post photos or videos, follow other users, comment and like other users' posts) generate diverse forms of data that result in multiple user relationship views. The proposed framework integrates user relationship learning under multiple views and the relationship strength modeling.
- Gong et al[44] proposed a semantic friend recommendation method based on the LDA algorithm and weighted average method. The authors considered the structure of the social network (ie, dynamic behaviors) and the static user attributes (semantic information, geographical location, and common friends).
- Zhu et al[45] proposed a trust prediction method based on identified trust clusters. The friends' recommendation is based on the trust value and the similarity among individuals. Then to improve the recommendation quality, the authors integrated user preference, geographical influence, and trust relationship.

2.4 | Discussion and research motivation

The study of the existing friends recommendation approaches has allowed us to come up with the following conclusions:

- Some existing trust-aware recommendation approaches are mainly based on trust-propagation or users' trust-based neighbors to detect communities of users. However, we should point out that trust information between users is rarely available in social networks. Thus, we find it more relevant to formalize and model the trust for a given user in the context of a social network taking into account his/her interactions with other users.
- To the best of our knowledge no work has yet addressed the user's credibility concept in the network, reflecting his/her degree of commitment (ie, participation and sociability) and his/her degree of trust based on his/her competency and seniority.
- The existing works shows that the social information provide more accuracy and personalized recommendation results as the users' favors are similar or influenced by their connected friends. Furthermore, the semantic aspects allow a more precise representation of knowledge. However, only few works integrated the social and semantic information with the CF algorithm.

In this article, we will focus on the following aspects:

- The modeling of a user's implicit profile through his/her interactions in the social network.
- The recommendation of potential friends to a given user based on an enhanced CF recommendation integrating the semantic and social information of users' profiles with the consideration of their credibility in the context of social networks (their degree of trust and commitment). The integration of users' credibility will distinguish our contribution from other already existing approaches that use the semantic and/or social aspects with the CF recommendation.

3 | THE PROPOSED SEMANTIC AND SOCIAL-BASED CF APPROACH

3.1 | Description of our approach

In order to take advantage from the social network information, our approach applies the user-user based CF technique enhanced with semantic and social dimensions (see Figure 1).

The semantic dimension looks for close friends for the active user u, who share with him, mainly, knowledge domains. The semantic filtering (SemF) is applied to calculate similarities between u and all other users and tries to suggest him only the users whose degree of similarity is greater than or equal to a given threshold. While the social dimension, calculates the social degree of users based on some social features such as their friendship and credibility degree in the social network.

The user's profile includes all the personal information (eg, name, date of birth, contact details, and so on) and more specific information such as the specialty, preferences, domains of interest, and expertise according to a certain degree, geographical localization, as well as the friends list and credibility degree in the social network.

Figure 2 illustrates the main components that describe the user's profile, considered in the proposed approach. These parameters can be exploited for the recommendation of both friends and items and are categorized into three dimensions: collaborative, semantic, and social, referring, respectively, to the three types of filtering: CF, SemF, and SocF.

3.1.1 | The user-user based CF

Two major techniques are used in traditional CF using rating information: (1) the memory-based methods compute the similarity between users' profiles based on ratings using similarity functions such as Pearson Correlation[21]; and (2) the model-based methods estimate items rating by training machine learning models on ratings data already provided.

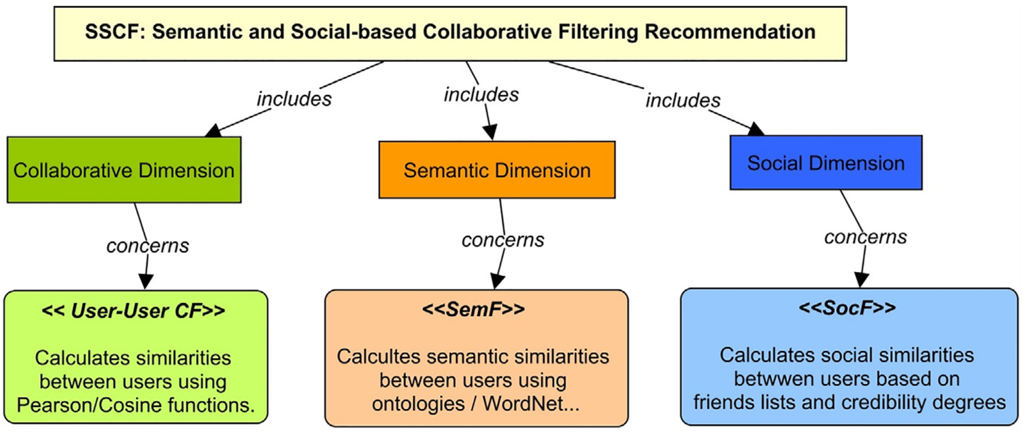

FIGURE 1 The semantic and social-based collaborative filtering approach [Colour figure can be viewed at wileyonlinelibrary.com]

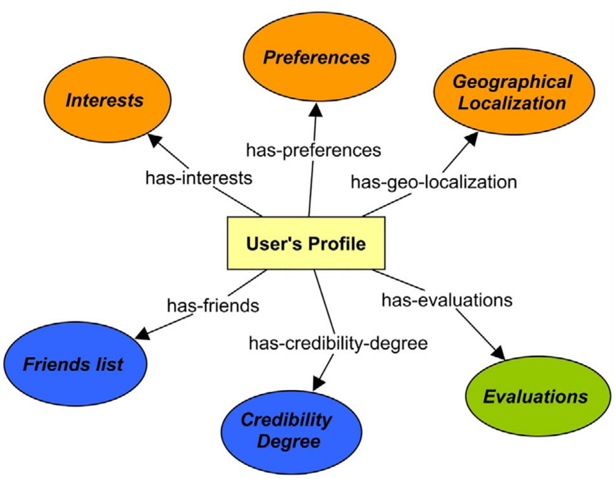

FIGURE 2 The main user's profile components [Colour figure can be viewed at wileyonlinelibrary.com]

We chose in this work a memory-based CF approach and used the user-user based recommendation. However, in our future work we envisage to apply a model-based CF algorithm by considering for example the well-known probabilistic matrix factorization (PMF) algorithm.

By using the user-user based CF algorithm, the system offers the possibility of identifying the best neighbors for a given user, using the usage matrix. The matrix can be constructed using the ratings of users on items (resources) and can be seen as a set of line vectors (see Figure 3). Calculating similarity between two users consists of measuring the similarity between the two vectors (for instance to calculate the similarity between the users U_1 and U_2, we calculate the similarity between the two vectors *Vector a* and *Vector b*).where:

$I_1, I_2 \ldots\ I_n$: represent a set of resources and $U_1, U_2 \ldots\ U_n$: represent a set of users.

Two functions were used to calculate the similarity between users: the Pearson correlation coefficient and the cosine function. According to Shi et al,[46] in most collaborative recommendation systems, these two similarity functions are utilized to provide recommendations considering the absolute ratings between users. The Pearson correlation is given by this formula[47]:

$$\mathrm{Sim}_{\mathrm{Pearson}}\ (U_a, U_b) = \frac{\sum_j (v_{a,j} - \overline{v_a})(v_{b,j} - \overline{v_b})}{\sqrt{\sum_j (v_{a,j} - \overline{v_a})^2}\sqrt{\sum_j (v_{b,j} - \overline{v_b})^2}}, \tag{1}$$

where:

$v_{a,j}$: represents the evaluation of the user a for the resource j.

$\overline{v_a}$: represents the average rating of the user a on all resources.

The correlation between users U_a and U_b is comprised between 1 and −1 ($-1 \leq \mathrm{Sim}_{\mathrm{Pearson}}\ (U_a, U_b) \leq 1$).

When this correlation is equal to the value 1, this means that they are highly correlated. While if the value is equal to −1, this implies that the users U_a and U_b have totally opposite opinions. A correlation equal to 0, means that the two users are considered to be independent.

The value calculated by the cosine function is between 0 and 1. It is given by the following formula:

$$\mathrm{Sim}_{\mathrm{Cosine}} = \sum_j \frac{v_{a,j}.v_{b,j}}{\sqrt{\sum_j (v_{a,j})^2\ \sum_j (v_{b,j})^2}}, \tag{2}$$

where:

$v_{a,j}$: represents the evaluation of the user a for the resource j.

The collaborative similarities between users using these two functions allow the identification of neighborhoods and therefore building communities of users who evaluate similarly according to a given threshold. However, evaluating items in the same way does not mean that two persons share domains of interest or even affinities. Thus, in order to take maximum advantage of the semantic knowledge representation and social information, we have thought about combining the traditional CF algorithm with semantic and social aspects.

3.1.2 | The semantic filtering

Two users u_1 and u_2 are considered as semantically close friends if the degree of closeness between them is greater than or equal to a given threshold. This means that a general similarity based on different parameters will be computed. Let us consider the followings parameters (see Figure 4):

- Sharing similar knowledge domains.
- Sharing similar preferences.

		I_1	I_2	I_3	…	I_m
Vector a	U_1	5	2	3	…	4
	U_2	4	1	1	…	0
	U_3	4	0	2	…	3
	…	…	…	…	…	…
Vector b	U_n	4	3	5	…	5

FIGURE 3 The user-user collaborative filtering approach [Colour figure can be viewed at wileyonlinelibrary.com]

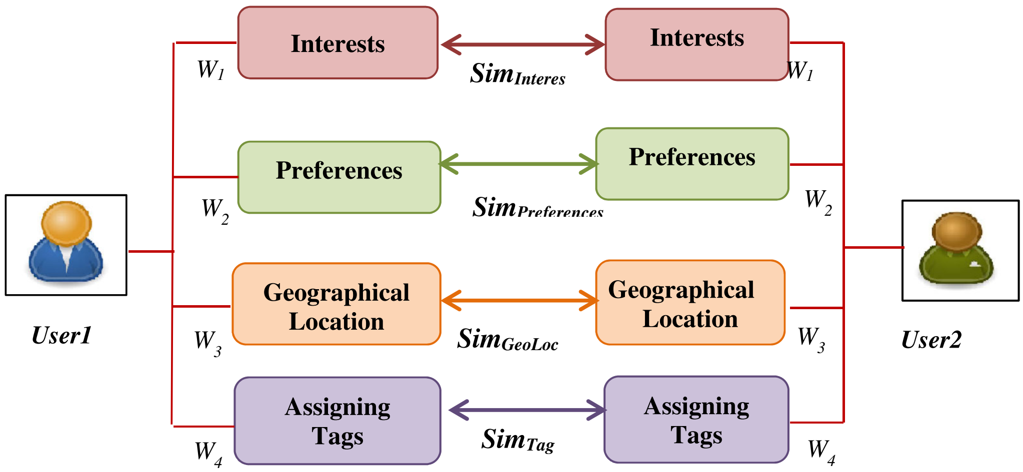

FIGURE 4 Similarity calculation between two users [Colour figure can be viewed at wileyonlinelibrary.com]

- Having similar geographical location.
- Assigning similar tags to items.

The global similarity is calculated using the following formula[48]:

$$\text{Sim}_{\text{global}}(u_1, u_2) = \frac{\sum_{i=1}^{\text{Nb}} \text{sim}_i(u_1, u_2) * W_i}{\text{Nb}}, \tag{3}$$

where: Nb: is the number of partial similarities; $\text{sim}_i(u_1, u_2)$: is the partial similarity; and W_i: refers to the weights that express a priority level, with: $\sum_i W_i = 1$.

Interests-based similarity ($Sim_{Interest}$): Corresponds to the similarity calculation between the active user u_1 and all other users, with respect to their domains of knowledge and using domain knowledge ontology (DKOnto) which describes the concepts related to the domain of interests (eg, software engineering, networking, and so on). DKOnto is a taxonomy used to express subsumption relationships between domains. For example, one can use the hierarchical ontology of computer science domain, which derives from the well-known ACM taxonomy: (http://www.acm.org/class/1998/). Figure 5 shows an excerpt of this ontology.

The user $u_1$and his friend u_2 can have several domains of interest. We construct a similarity matrix, where the lines represent all the domains D of u_1, while the columns represent all the domains D' of u_2. The calculation of the matrix elements is performed using the Wu and Palmer[49] similarity metric, as follows:

For each domain D

For each domain D'

/*calculate de similarity between D and D'*/

$$\text{sim}(D, D') = \frac{2 * \text{Depth}(D_c)}{\text{Depth}(D) + \text{depth}(D')}, \tag{4}$$

End For

End For

where:

D, D': represent, respectively, the domain of u_1 and the domain of u_2.

Depth (D) is the depth of D; Depth (D') is the depth of D'.

D_c is the closest common parent to D and D'.

Let us consider the similarity between the two domains "Tools" and "Software architecture," using the Wu and Palmer similarity measure:

$$\text{Sim (Tools, Software architecture)} = \frac{2 * \text{profondeur(software\_engineering)}}{\text{profondeur(Tools)} + \text{profondeur(Software\_architecture)}} = \frac{2 \times (3)}{(5) + (4)} = \frac{6}{9} = 0.66.$$

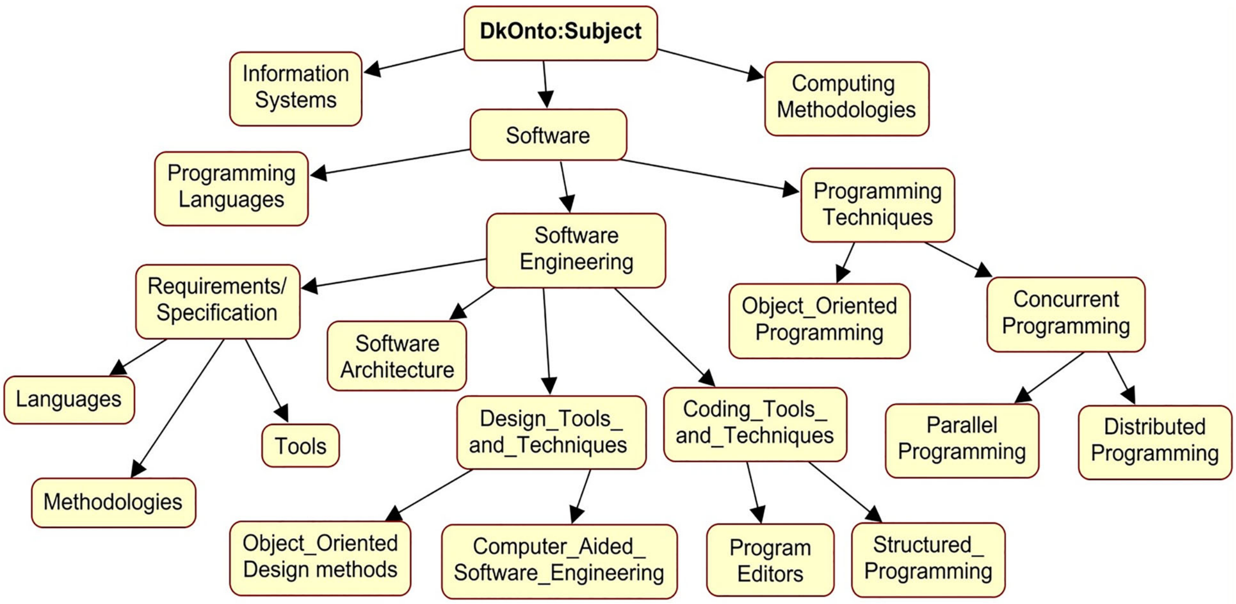

FIGURE 5 Excerpt of the computer science domain ontology [Colour figure can be viewed at wileyonlinelibrary.com]

Finally a global similarity is obtained by calculating an average of the matrix elements:

$$\mathrm{Sim}_{\mathrm{Interests}}(u_1, u_2) = \frac{1}{N} \sum_{i=1}^{M} \mathrm{Sim}(D_i, D_j), j = 1..N. \quad (5)$$

Preferences-based similarity (Sim$_{Preferences}$): Preferences refer to the attributes of the most evaluated items by the user. Each preference is represented by a couple (Name of preference: Number of reviews carried out).

$$\text{Preferences } (u) = \{(a, n) \mid n > 0\}, \quad (6)$$

where: a is an item attribute and n is the number of ratings made by u for a.

The similarity is calculated with the generalized Jaccard index, as follows:

$$\mathrm{Sim}_{\mathrm{Preferences}}(u_1, u_2) = 1 - \frac{\sum_{a\in A}\min(n_a, m_a)}{\sum_{a\in A}\max(n_a, m_a)}, \quad (7)$$

where;

A is the set of all the preferences of u_1 and u_2;

n_a is the number of reviews made by u_1 on the attribute a; and.

m_a is the number of reviews made by u_2 on the attribute a.

Geographical locations-based similarity (Sim$_{GeoLoc}$): Geographical information reflects a users spatial characteristics. The locations of items evaluated by the user are considered in order to find the locations that the user frequents the most. This information is described as follows:

$$\text{Locations } (u) = \{(\text{latitude}, \text{longitude}, n) \mid n > 0\}, \quad (8)$$

where: n is the number of times u has reviewed the item corresponding to this pair of (latitude, longitude).

The similarity calculation will be done in the same way as with the domains of interest. As we are interested in this article by the recommendation of users, we ignored this parameter in the calculation of the semantic similarity and therefore in the recommendation algorithm (unless we would like to recommend people who are interested in the same geographic locations). This information may be of primary interest in the case of recommendation of items where it would be interesting to take into account the geographical location (example for the recommendation of restaurants, it is necessary to take into account this information).

Tag-based similarity (Sim_{Tag}): Means assigning similar tags to same items. Among textual data in social networks, tags are the most used for the recommendation. A tag is a keyword or term associated with or assigned to an item, describing a characteristic of the object and allowing easy clustering of information containing the same keywords. A formal vocabulary using WordNet is used to measure the semantic distance between pairs of tags (the synonymy relationship between tags' peers will be exploited in this case). The user u_1 and his friend u_2 are considered as close, if they have tagged similarly same items according to a similarity threshold value:

$$\text{sim}_{\text{Tag}}(u_1, u_2) = \frac{\text{Nb Similar} - \text{Tags}\ (u_1, u_2)}{\text{Nb\_total\_tags}(u_1)}, \tag{9}$$

where:

Nb Similar – Tags (u_1, u_2): is the number of items tagged with similar tags by u_1 and u_2;

Nb_total_tags(u_1): is the number of tags used by the user $u_{1.}$

3.1.3 | The social filtering

The main idea is to consider recommendations based on social friendship metrics. We identify two metrics: (1) *the friendship;* and (2*) the credibility degree*. We have considered two parameters for calculating the degree of credibility of an active user u_1: his *Commitment* and *trust* degrees.

1 ***Friendship metric***. This metric computes the similarity weight between two users $\boldsymbol{u_1}$ **and** $\boldsymbol{u_2}$, based on their social relationships which is defined as the size of the intersection divide by the size of the union of friend sets:

$$\text{Sim}_{\text{soc}}(u_1, u_2) = \frac{F(u_1) \cap\ F(u_2)}{F(u_1) \cup F(u_2)}, \tag{10}$$

where: $F(u_1)$, respectively, $F\ (u_2)$: represent the number of friends of u_1, respectively, u_2.

2 **Commitment degree.** Two parameters are considered: (1) *the participation degree* of an active user u, including the degree or rate of evaluations he carried out; and (2) *the sociability degree* represents his friendship rate in the social network.

$$\text{Commitment}\ (u) = \alpha_1\ .\ \text{Participation}(u) + \beta_1\ .\ \text{Sociability}(u), \tag{11}$$

where: α_1 and β_1 are weights that express a priority level, with $\alpha_1 + \beta_1 = 1$

- *The participation degree of the user u:* concerns mainly the degree of performed evaluations by u. This degree is calculated based on the number of evaluations performed by *u,* NbEval (u), according to all the evaluations carried out in the system, NbTotalEval.

$$\text{Participation}\ (u) = \frac{\text{NbEval}(u)}{\text{NbTotalEval}}. \tag{12}$$

- *The sociability degree of the user u:* this degree is calculated based on the number of friends of u according to all the registered users of the social network.

$$\text{Sociability}\ (u) = \frac{\text{NbFriends}(u)}{\text{NbUsers} - 1}. \tag{13}$$

3 Trust degree of the user u. This metric takes into account the seniority level of u and his degree of competence in the social network using the following formula:

$$\text{Trust}(u) = \alpha_2 \,.\, \text{Seniority}(u) + \beta_2 \,.\, \text{Competency}\ (u), \tag{14}$$

where: α_2, β_2 are weights that express a priority level, with $\alpha_2 + \beta_2$=1

- *The seniority level of the user u:* is calculated based on the date of his registration in the social network.

$$\text{Seniority}\ (u) = \frac{\text{Current date} - \text{Registration date of } u}{\text{Curent date} - \text{Social Network starting date}} \tag{15}$$

- *The Competency degree of u:* is calculated on two steps, based the following assumption: *"A friend is competent if he has evaluated correctly the resources compared to their average evaluations in the social network"*:
- ***Step 1:*** Calculate the competency degree of a friend F regarding a given item R_j. We start by calculating the average of ratings for each item. Then, we compare the rating given by F for the same item with the average value.

$$\text{Competency}(F, R_j) = \begin{cases} \frac{\text{avg}(R_j)}{v_{i,j}} & \text{if Avg}(R_j) \leq v_{i,j} \\ \frac{v_{i,j}}{\text{avg}(R_j)} & \text{if } v_{i,j} \leq \text{Avg}(R_j) \end{cases}, \tag{16}$$

where:

avg(R_j): is the average evaluation of the item regarding all the users.
$v_{i,j}$: is the evaluation of the friend F for R_j

- ***Step 2:*** Calculate the global competency degree of the friend, using this formula:

$$\text{Competency}\ (F) = \frac{1}{n} \sum_{j=1}^{n} \text{Competency}(F, R_j), \tag{17}$$

where: n represents the number of items evaluated by the friend.

3.2 | Recommendation algorithm

Based on the proposed approach, the following recommendation algorithm suggests a list of the most suitable potential friends according to the profile of the user. We present the semantic and social-based CF (SSCF) recommendation algorithm, as follows:

Algorithm 1. SSCF Recommendation Algorithm

```
Input:
  User's profile (u' Profile), Rating matrix
Output:
  Rec-list /* A list of recommended friends for a given user u */
Begin
  Rec-list: =∅;
  If u is a new user Then
      Rec-list:= Rec-list ∪ {list of leaders}
  Else
   If not enough ratings Then
    SemSocF (u) /* combines the SemF and the SocF */
```

Else
SSCF (u) /* combines the CF with the SemF and the SocF*/
End If
End If
Sort Rec-list (u);
Display (u, Rec-list) /* Display a list of recommended users in a given order*/
End.

The SemSocF algorithm is applied in case the user has not made enough evaluations. It combines the SemF and the social filtering (SocF) algorithms according to different hybridizations: The *Sem-based SocF* (resp. the *Soc-based SemF*) to see the contribution of semantics on SocF (resp. the contribution of social information on SemF). The principle of the *Sem-based SocF* algorithm, recommends the list of socially close friends to u, considering the list of semantically close friends to u). Whereas, the *Soc-based SemF* algorithm (SemF based on social information) consists in recommending the list of semantically close friends to u, considering the list of socially close friends to u.

In the case the user u has friends but his profile is not sufficiently informed then the SocF algorithm will be applied. Likewise, if the user u has an informed profile (a preference and/or interest list is available) but has not yet added any friends then the SemF algorithm will be applied.

On the other hand, the SSCF algorithm which combines the CF algorithm with the semantic and social algorithms will be applied if there are enough evaluations (ie, in this case the CF is applicable). We have considered the following combinations between the three algorithms (CF, SemF, and SocF):

- The *Sem-based* CF (resp. the *Soc-based* CF*)* to see the contribution of semantics on the CF recommendations (resp. to see the contribution of social information on the CF recommendations). The neighborhood calculation in the CF will be based on the list of semantically close friends for the Sem-based CF algorithm (respectively, the neighborhood calculation in the CF will be based on the list of socially close friends for the Soc-based CF algorithm).
- The *Sem-Soc-based* CF to see the contribution of semantics and social information on the CF. In this case, the neighborhood calculation in the CF will be based on the list of semantically and socially close friends.

The aforementioned hybrid algorithms are based on the basic recommendation algorithms: the SemF (Algorithm 2), the SocF (Algorithm 3) and the CF (Algorithm 4), which are described as follows:

Algorithm 2. SemF (u)

Input: UserTable /*contains all the users of the social network that are not friends with u */
Output: RecSem-list /* A list of recommended friends for u that are semantically close to u */
BEGIN
Rec-list: =∅;
For each user u' from UserTable **Do**
Calculate $Sim_{Sem}(u, u')$;
If $Sim_{Sem}(u, u' >= Threshold_{Sem}$ **Then**
RecSem-list: = RecSem-list ∪ {u'}
End If
End
END.

The SocF algorithm is described as follows:

Algorithm 3. SocF (u)

Input: UserTable /*contains all the users of the social network that are not friends with u */
Output: RecSoc-list /* A list of recommended friends for u that are socially close to u */
BEGIN
Rec-list: =∅;

For each user u' from UserTable **Do**
Calculate $Sim_{Soc}(u, u')$;
If $\mathrm{Sim}_{\mathrm{Soc}}$(u, u' >= $\mathrm{Threshold}_{\mathrm{Soc}}$ **Then**
RecSoc-list: = RecSoc-list ∪ {u'}
End If
End
END.

Finally, the CF is described by the following algorithm:

Algorithm 4. : CF (u)

Input: UserTable /*contains all the users of the social network that are not friends with u */
Output: RecCF-list /* A list of recommended friends for u which similarly evaluated the same items as u */
BEGIN
Rec-list: =∅;
For each user u' from UserTable **Do**
Calculate $Sim_{CF}(u, u')$;
If $Sim_{CF}(u, u') >= Threshold_{CF}$ **Then**
RecCF-list: = RecCF-list ∪ {u'}
End If
End
END.

4 | IMPLEMTATION AND EXPERIMENTAL RESULTS

In the following section we conduct an empirical study based on the proposed recommendation approach and the use of the Yelp database. This section will be structured as follows: (1) a description of our user recommendation system; (2) the evaluation and results analysis; and (3) a discussion that highlights the main results and analysis as well as some directions for future work.

4.1 | The users' recommender system

The development of our users' recommender system has been done using the Java J2EE platform, in the form of web application. Several tools were used including: the editor Protégé for the creation of the ontology, the Jena API to operate the OWL files, the PostgreSQL DBMS for creating the database, the Java language using the NetBeans IDE. We used the JSP and Servlet technologies respecting the MVC standard (Model, View, and Controller). Our application was deployed with the Apache Tomcat server that is both HTTP server and servlet/JSP container. Figure 6 shows the main interface of the users' recommendation system.

Figures 7 and 8 illustrate the parameters that are required for the execution of the SocF and SSCF recommendation algorithms. For the SocF, for instance, we can choose only one of the parameters (eg, friendship) or two parameters (eg, Friendship and Trust with Seniority and/or Competency) or the three parameters (ie, Friendship, Commitment, and Trust). The “Recommendation” button allows to display the list of recommended users for the active user (User1), depending on the parameters that have been chosen. The users who will be displayed will be those socially close to User1, according to a given social threshold. The “Evaluation” button is used to launch the evaluation of the SocF algorithm by considering all the users of the social network.

Similarly, the following figure shows the parameters to be considered in the hybridization of the three algorithms (CF, SemF, and SocF) by introducing the degree of importance and the similarity threshold of each of the algorithms.

4.2 | Evaluation

In order to evaluate the performance of our approach, we performed several tests and experiments on the proposed algorithms.

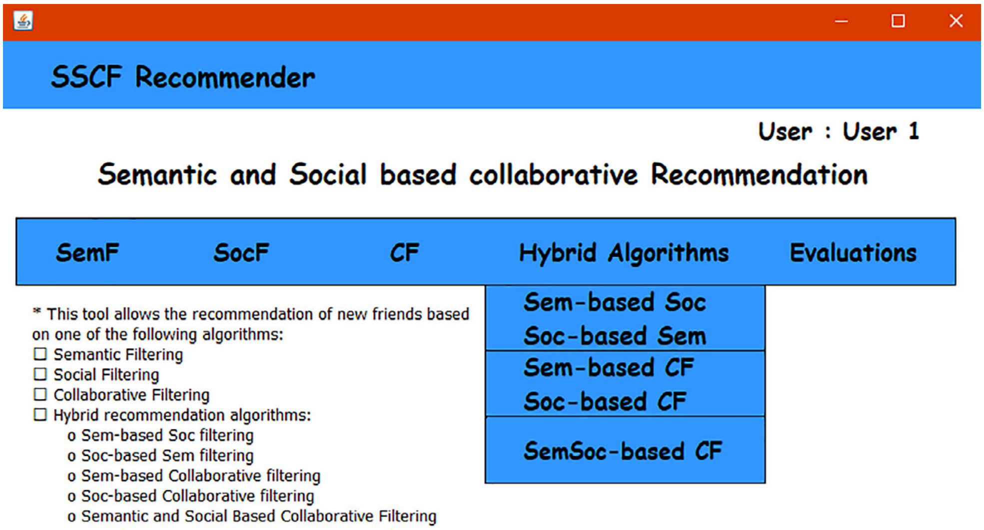

FIGURE 6 Interface of the users' recommender system [Colour figure can be viewed at wileyonlinelibrary.com]

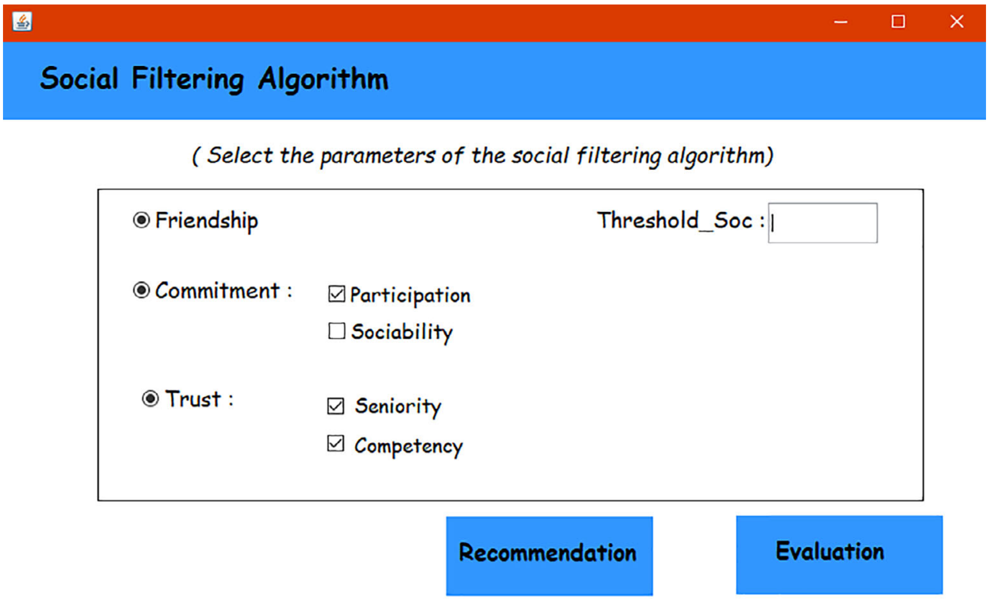

FIGURE 7 Interface of the social filtering algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

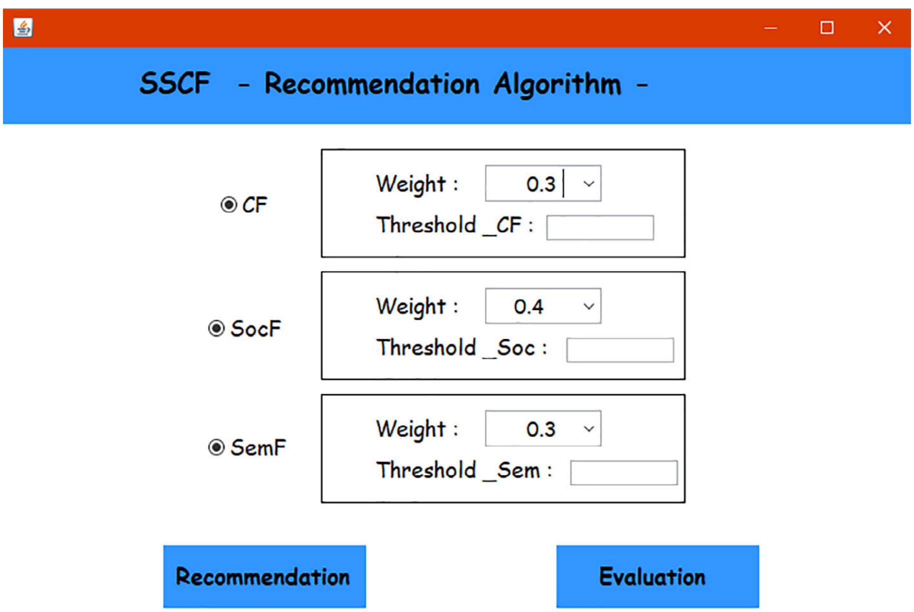

FIGURE 8 Interface of the hybrid social-based collaborative filtering recommendation algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

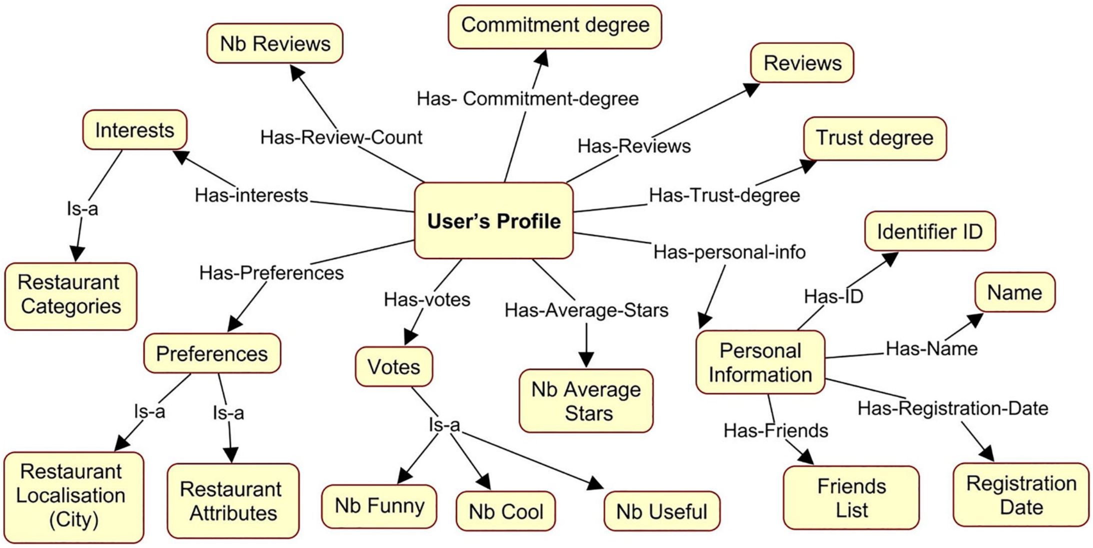

FIGURE 9 Conceptual model of the user's profile [Colour figure can be viewed at wileyonlinelibrary.com]

4.2.1 | Conceptual modeling and dataset

For the evaluation of our approach, we performed a set of experiments on the Yelp* social network whose main objective is to connect people with local businesses. We have chosen the "restaurant" category of Yelp as this is the most frequent category in this social network. A conceptual modelling was first done on the data of the Yelp social network.

Figure 9 illustrates the conceptual model for the user's profile.

We have exploited the users' interaction records to complete the definition of profiles. The implicit information of a given user consists of his interests and preferences, the number of his evaluations and collected (funny, useful, cool) votes, the average number of stars (he has assigned to the restaurants he has evaluated), his involvement, and trust degrees. On the other hand, implicit information of a given restaurant at a time *t* consists of the total number of assessments done on it and the average number of stars it has received.

The study of the Yelp database showed that many restaurants have attributes that others do not have. Thus, we have only kept the most frequent and relevant ones: "Expensive," "Good For Groups," "Outdoor Seating," "Take-out," "Late-night," "Good for Kids," "Garage," "Street," "Delivery," "Accepts Credit Cards," "Classy," "Romantic," "Wi-Fi," and so on.

Figure 10 describes the conceptual model of the item (restaurant).

Figure 11 presents an excerpt from the ontology of restaurant categories. The domain ontology describes a hierarchy of concepts "restaurants categories." Four levels are considered in our proposition as illustrated by this figure.

The experiments carried out aim to confirm the enhancement of the hybrid recommendation approach, specifically, in terms of improving the recommendation accuracy compared with the CF. Three main objectives are considered:

1. Show the importance of adding semantic and/or social information in the recommendation process (combining semantic and/or social information with the CF algorithm);
2. Compare the different combinations we have proposed in the previous section; and
3. Show the importance of considering the credibility information in the recommendation.

Before using the Yelp Database, we have performed some pretreatment operations for the inclusion of implicit data (ie, interests, preferences, commitment and trust degrees, average rating and number of assessments per restaurant, and so on). The resulting database includes 4823 restaurants, 65 categories, and 5436 members who have performed 118 709 assessments on these restaurants (only members who have evaluated more than nine restaurants have been considered). Furthermore, we have performed some statistical analysis on the database:

*http://www.yelp.com/

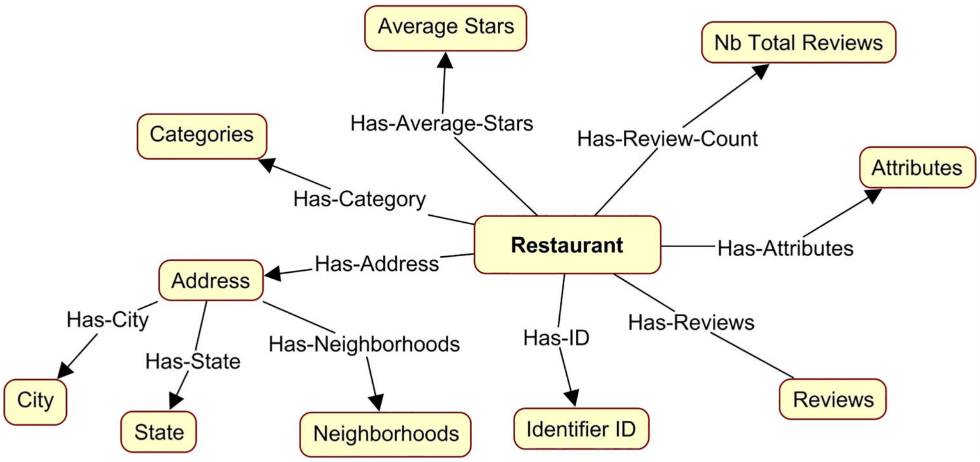

FIGURE 10 Conceptual model of the item (restaurant) [Colour figure can be viewed at wileyonlinelibrary.com]

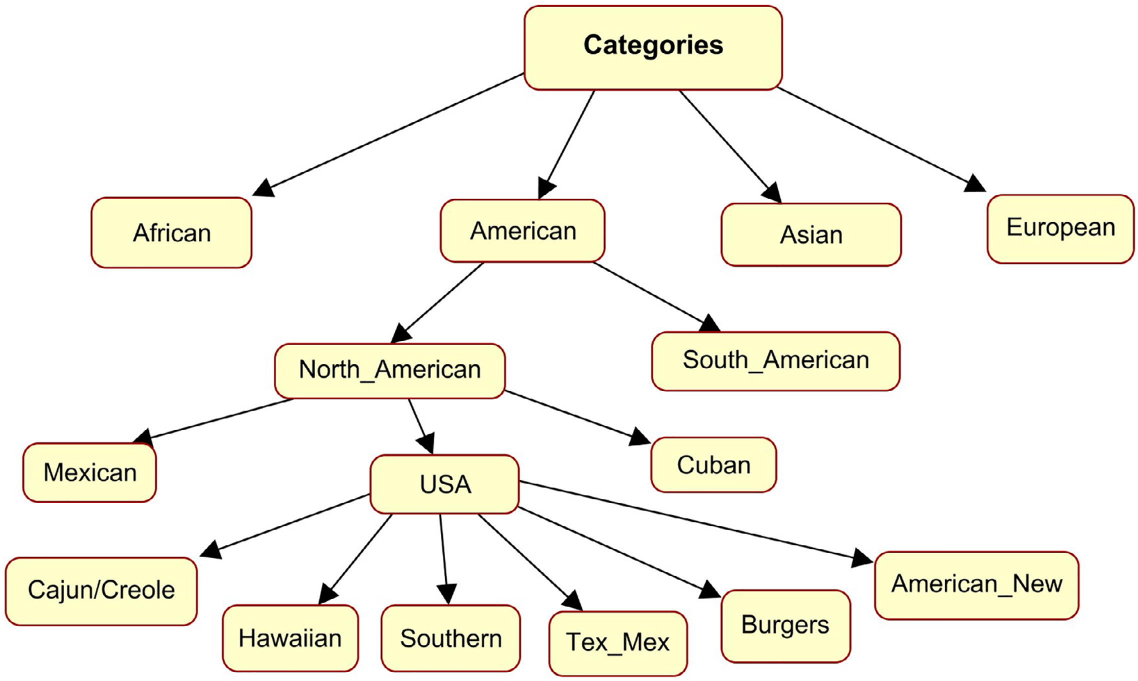

FIGURE 11 Excerpt from the ontology of restaurant categories [Colour figure can be viewed at wileyonlinelibrary.com]

- Average number of friends per user (Average friendship rate): 21.140912 ≅ 21.
- Average number of categories per user: 11.266556 ≅ 11.
- Average number of evaluations per user: 21.837564 ≅ 22.
- Average number of evaluations per restaurant: 24.613104 ≅ 25.

4.2.2 | Evaluation metrics

We considered the following evaluation metrics: Precision (P - measures the relevance of the recommendations), Recall (R - measures the ability of the system to make relevant recommendations), and F-measure (F - combines P and R metrics).

$$P = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalsePositive}}, \tag{18}$$

$$R = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalseNegative}}, \tag{19}$$

$$F = \frac{2 * P * R}{P + R}, \tag{20}$$

where:

- True positives (TP): represents the number of recommendations made to members who were originally friends.
- True negatives (TN): represents the number of recommendations that are not made to members who were not initially friends.
- False positives (FP): represents the number of recommendations made to members who were not initially friends.
- False negatives (FN): represents the number of recommendations not made to members who were initially friends.

4.2.3 | Evaluation results

Preliminary assessments. We evaluated the basic recommendation algorithms (CF, SemF, and SocF) by varying the similarity threshold values of each algorithm from 0.1 to 0.9 as well as the values of the different weights in order to keep the best values for the rest of the evaluations. The following are the first evaluations we have performed:

- The user-based CF, using the Pearson and Cosine similarity functions, where the best accuracy of the CF was obtained with the similarity threshold value of 0.4.
- The SemF, by varying the weights of the different partial similarities. The results of the tests carried out revealed that the combination $w_1 = 0.5$; $w_2 = 0.3$; $w_3 = 0.2$ gives the best results in terms of precision and F-measure where: w_1, w_2, and w_3 represent, respectively, the weights of the following partial similarities: sharing similar knowledge domains; sharing similar preferences; and having similar geographical location.
- The SocF, by varying the weights of the different parameters. For instance, the results of the tests carried out revealed that the combination $\alpha = 0.3$; $\beta = 0.3$; $\gamma = 0.4$ gives the best results in terms of precision and F-measure where: α, β, and γ represent, respectively, friendship, commitment, and trust degrees parameters.

Evaluation of hybrid algorithms. We evaluated the different combinations between the SemF and the SocF (ie, the Soc-based SemF and the Sem-based SocF) as well as the different combinations between the CF, the SemF and the SocF (ie, the Sem-based CF; the Soc-based CF, and the SSCF algorithms).

In order to show the contribution of the semantic information on the SocF, we compared the Sem-based SocF and the SocF algorithms. Figure 12 presents the precision and F-measure of the two algorithms.

We can notice from this evaluation that the integration of semantic information on SocF has improved the performance of the recommendation algorithm (we got better recommendation accuracy in terms of precision and F-measure values).

Furthermore, in order to show the contribution of social information on the SemF, we compared the Soc-based SemF and the SemF algorithms. Figure 13 and presents the precision and F-measure of the two algorithms. We can notice from this evaluation that the integration of social information on SemF has improved the performance of the recommendation algorithm (we got better recommendation accuracy in terms of precision and F-measure values).

Finally in order to show the contribution of the semantic and social information on the CF, we performed an experiment based on the hybridization of the three algorithms, that is, the SSCF algorithm. Figure 14 illustrates the Precision and F-measure of the different algorithms by varying the threshold value from 0.1 to 0.9 for each algorithm.

We can see that the SSCF gives a better performance compared with the CF and the other algorithms. The integration of semantics and social information enhanced the CF recommendation accuracy as summarized in Table 1. The results obtained by the different experiments, in terms of average precision, average recall and average F-measure. These results demonstrate the contribution of the hybrid approach compared with the standard CF algorithm.

TABLE 1 Summary of the experiment results

Algorithm	CF	SemF	SocF	Sem-based SocF	Soc-based SemF	SSCF
Avg-Precision	0.425	0.179	0.204	0.338	0.333	**0.493**
Avg-Recall	0.181	0.330	0.313	0.429	0.376	**0.891**
Avg-*F*-measure	0.625	0.232	0.247	0.378	0.353	**0.648**

Abbreviations: CF, collaborative filtering; SOCF, social-based collaborative filtering.

Evaluation of the importance of credibility information. We evaluated the hybrid SSCF algorithm by considering different combinations: (1) the hybrid algorithm, combining the CF, the SemF, and the SocF based only on the friendship parameter (SSCF-Friendship); (2) the hybrid algorithm, combining the CF, the SemF, and the SocF based only on the trust information (SSCF-Trust); and (3) the hybrid algorithm, combining the CF, the SemF, and the SocF based on both, the friendship and the credibility parameters (SSCF). We obtained the best values with the SSCF approach in terms of precision, recall and F-measure compared to the other algorithms. These values have been highlighted in bold in Table 1. Figure 15 illustrates the results we have obtained:

4.3 | Discussion

One of the most important challenges in social networking services is how to recommend appropriate friends to users. We were interested in this article by this issue taking into account two contributions: (1) the enhancement of the CF algorithm

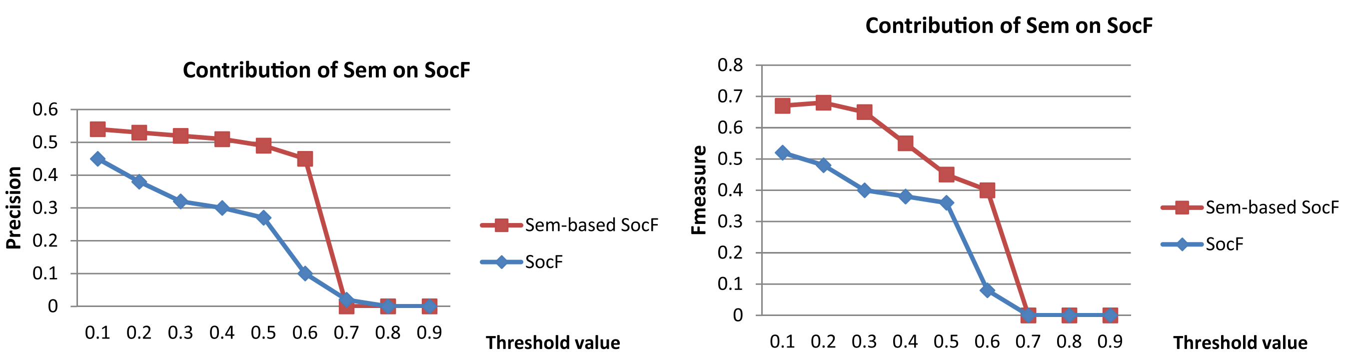

FIGURE 12 Precision and *F*-measure of the Sem-based SocF and the SocF algorithms [Colour figure can be viewed at wileyonlinelibrary.com]

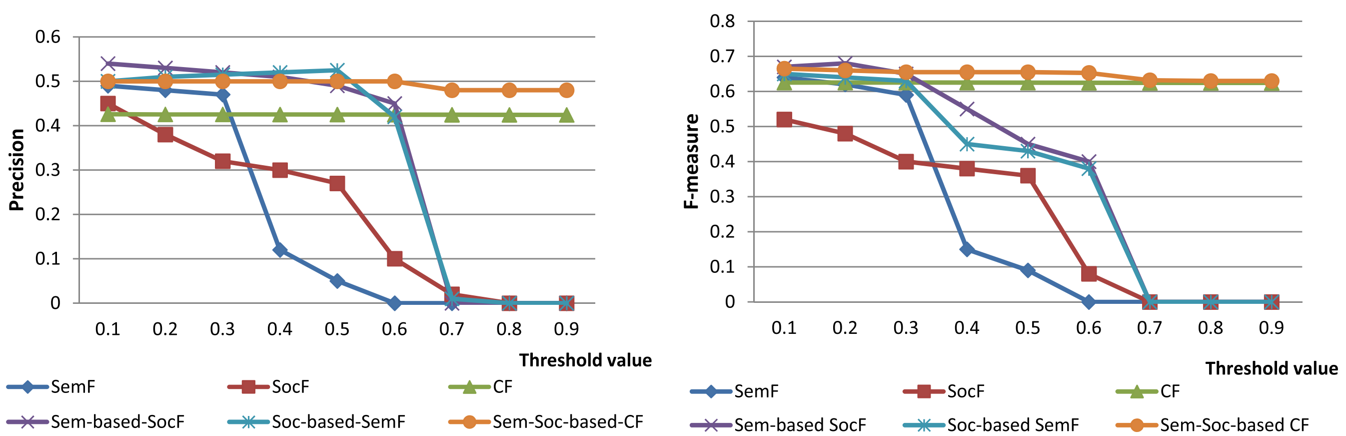

FIGURE 13 Precision and *F*-measure of Soc-based SemF and SemF [Colour figure can be viewed at wileyonlinelibrary.com]

with semantic and social information; and (2) the integration of credibility information in the users' recommendation algorithm.

4.4 | Interpretation of the results

The results of the experiments carried out show the contribution of the hybrid approach that combines the semantic and the social information with the user-based CF algorithm. On the other hand, the comparison of SocF and Sem-based SocF shows the contribution of the semantic information for the improvement of the SocF and likewise, the comparison of the SemF and Soc-based SemF shows the contribution of the social information on the SemF which improves its performance. The in-depth reading and interpretation of these results show that the integration of the semantic information in the recommendation process allows the recommendation of friends sharing similar interests and preferences with the active user (ie, considering the semantic profile of users). Similarly, the integration of social information in the recommendation process allows the recommendation of friends with social close affinities (ie, considering the social profile of users).

On the other hand, the combination of semantic and/or social information with the standard CF algorithm solves the cold start problem from which the CF suffers. Even with an insufficient number of evaluations, the system will be able to recommend new friends based on the semantic and/or social information. If any user has friends but has not yet made any evaluation, then the system can recommend other users to him/her based only on the social dimension that includes, in this case, the friendship and the sociability and seniority parameters of the credibility information (ie, only the sociability and seniority could be used). Similarly, if a user has performed a number of assessments but has not yet added any friend, then the system can recommend other people to him/her based on an enhanced CF, combining the semantic dimension and some features of the social dimension (the participation and the competency parameters of the credibility information).

Finally, we demonstrated the importance of the credibility information in the recommendation algorithm. The results obtained in terms of the recommendation accuracy, show that the hybrid algorithm SSCF that includes both features, friendship and credibility outperforms the two other hybrid algorithms, based on friendship (SSCF-Friendship) and on trust information (SSCF-Trust) for the social dimension.

4.5 | Generalization of our approach and future extension

The proposed approach could be useful for all domains and can be adapted, for instance, to a professional or research social network considering items, products, articles, or books. The preferences will represent the areas of interest, while the social aspect remain also applicable since the concepts of friendship, commitment, and trust are possible to interpret in other domains as well. The adaptation consists to consider the information available and to ignore those that are not available. The proposed models could be extended by including other information such as: (1) the tags and annotations for

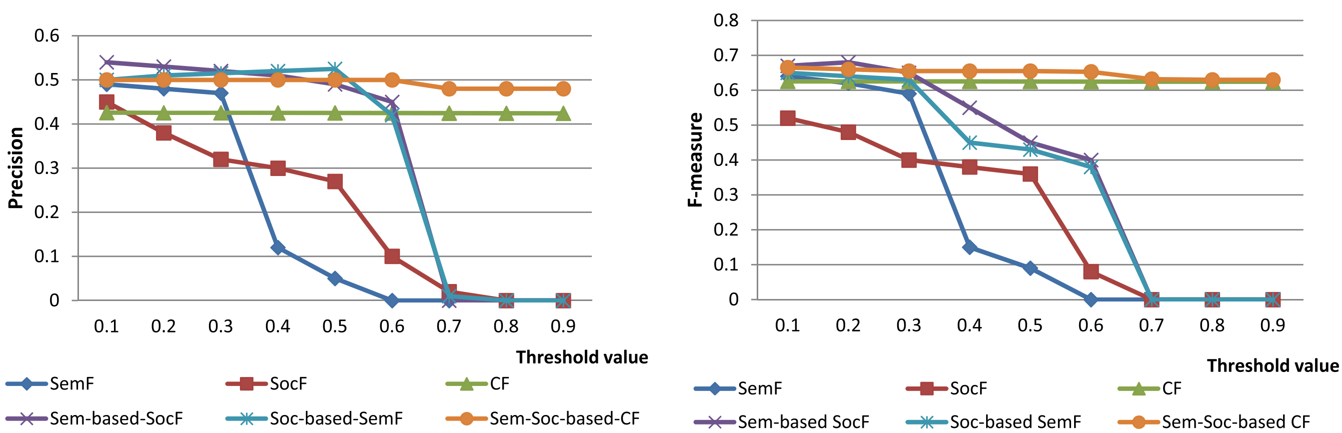

FIGURE 14 Precision and *F*-measure of the different algorithms [Colour figure can be viewed at wileyonlinelibrary.com]

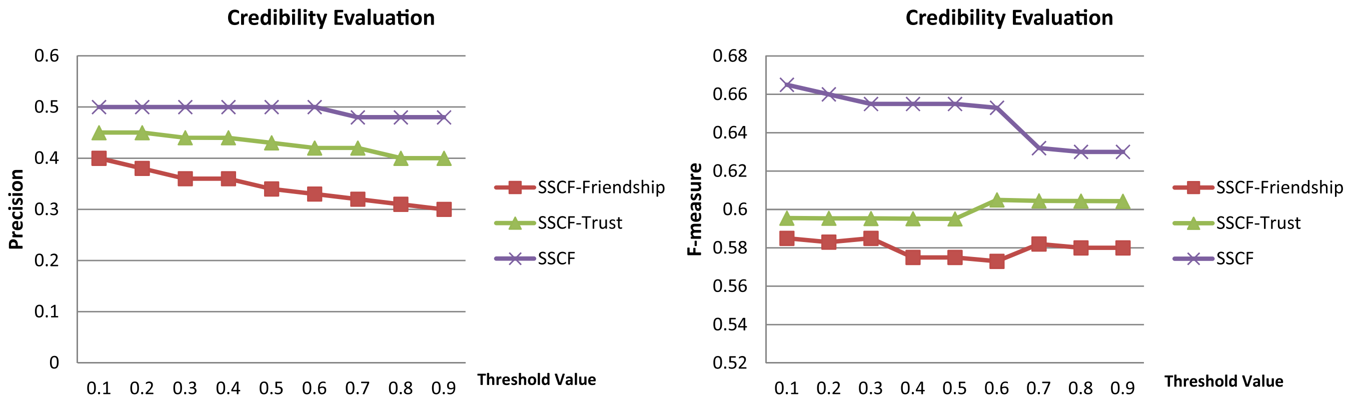

FIGURE 15 Contribution of the credibility information in the recommendation [Colour figure can be viewed at wileyonlinelibrary.com]

the semantic dimension; and (2) the consideration of immediate and distant friends for the friendship and the integration of the influence in the credibility information, for the social dimension.

The results obtained using the well-known YELP database are promising. Nevertheless our approach could be enriched according to different possible extensions:

1. *The automatic assignment of weights:* we have empirically evaluated various combinations of the weights of the parameters related to the semantic, social, and collaborative algorithms. Performing an automatic optimization of the values of these weights (using machine learning or optimization algorithms) should improve the recommendation accuracy.
2. *The enrichment of the proposed models:* other kinds of information can be included in our models using for example tags and annotations[7] as well as the immediate/distant friends,[4] the influence,[50,51] and the local/global trust.[52]
3. *Solving the problem of sparsity:* As the CF faces issues with sparsity of rating matrix and growing nature of data, these challenges are well taken care of by matrix factorization. Accordingly, we believe that using different matrix factorization models such as singular value decomposition (SVD) and PMF will alleviate the data sparsity problem and improve the recommendation quality.

Moreover, many other enrichments could be proposed in the future including for example the use of classification and clustering techniques. In previous work on items recommendation[53] that combines the CF and the SocF (the friendship metric is used in this work) algorithms using a multiview clustering have given better recommendation accuracy. We believe that the use of clustering and classification techniques in the proposed friends recommendation approach to group similar users according to the semantic, social, and collaborative views will provide better recommendation accuracy. Furthermore, other semantic similarities could be used such as semantic similarity measure based on semantic information in the linked open data knowledge base.[54]

5 | CONCLUSION

We presented in this work an enhanced CF approach for the recommendation of friends in social networks. Our approach takes into consideration the semantic and social information of users. These two dimensions have been formalized and a recommendation algorithm is proposed using different hybridization between the collaborative, the semantic, and the SocF. The main contributions of the semantic and social-based collaborative recommendation approach are: (1) the modeling of the implicit user's profile through his/her interactions in the social network; and (2) the modeling of the user's credibility information, which is based on his/her trust and commitment in the social network. The parameters involved in the computation of credibility play an important role in enhancing the recommendation accuracy and effectively tackling the cold start problem. This approach can be exploited by other works, with some adaptations and enrichments as discussed previously. The evaluation results, using the Yelp social network, show that the integration of the semantic and social information with the CF algorithm gives a better recommendation accuracy compared with the user-based CF algorithm. Moreover, this combination alleviates the cold-start problem as the system may suggest to a given user a list of other appropriate users considering the semantic and/or social information (even if the system does not find enough evaluations made by the active user). Finally, the experimentation demonstrated the added-value of the credibility information in the recommendation algorithm.

The strengths of this article a,s mentioned above, concern mainly the following contributions: (1) the improvement of the recommendation accuracy of the CF algorithm and the resolution of the cold start problem thanks to the integration of the semantic and social information; and (2) the modeling of the user's implicit profile including the credibility information. However, some limitations and shortcomings can be identified giving rise to several future perspectives on both research and practical levels. One potential limitation to the present work is the performance of the recommendation algorithm which could be reduced with the increasing data in the social network. Accordingly, we plan to adapt our approach to the big data context, by dealing with large scale data. To this end, it would be interesting to consider clustering techniques, by adopting a multiviews clustering approach for grouping users. Previous work using CF with friendship and trust information based on multiviews clustering has enhanced the performances of the algorithm.[53,55] Another limitation of our approach is the use of the user-based CF algorithm which does not solve the sparsity problem due to the lack of users' assessments. For future research, to alleviate this problem, we intend to develop other variants of the CF using different matrix factorization models such as PMF or SVD++. Moreover, in order to improve the quality of the recommendations, we believe that other kinds of information could be included in our models such as the immediate/distant friends, the influence and the local/global trust information. On the other hand, in our future work, we also envisage to test our approach in a real setting for the recommendation of semantically and socially close friends (in an online collaborative learning environment for example). A qualitative and quantitative assessment based on users' feedback will allow a more in-depth evaluation of the recommendation system. Finally, from a practical point of view, our approach could be applied by practitioners for people recommendation in professional, business, or learning/research social networks. We believe that our approach would be of considerable benefit for them. The recommendation of people sharing common interests and having a given credibility degree in the network would strengthen links between members and encourage exchanges and active collaboration between them. Moreover, other types of recommendation could be derived from our approach such as the recommendation of items (eg, products, articles, or documents) and services.

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