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HCoF: Hybrid Collaborative Filtering Using Social and Semantic Suggestions for Friend Recommendation

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Abstract: Today, people frequently communicate through interactions and exchange knowledge over the social web in various formats. Social connections have been substantially improved by the emergence of social media platforms. Massive volumes of data have been generated by the expansion of social networks, and many people use them daily. Therefore, one of the current problems is to make it easier to find the appropriate friends for a particular user. Despite collaborative filtering's huge success, accuracy and sparsity remain significant obstacles, particularly in the social networking sector, which has experienced astounding growth and has a large number of users. Social connections have been substantially improved by the emergence of social media platforms. In this work, a social and semantic-based collaborative filtering methodology is proposed for personalized recommendations in the context of social networking. A new hybrid collaborative filtering (HCoF) approach amalgamates the social and semantic suggestions. Two classification strategies are employed to enhance the performance of the recommendation to a high rate. Initially, the incremental K-means algorithm is applied to all users, and then the KNN algorithm for new users. The mean precision of 0.503 obtained by HCoF recommendation with semantic and social information results in an effective collaborative filtering enhancement strategy for friend recommendations in social networks. The evaluation's findings showed that the proposed approach enhances recommendation accuracy while also resolving the sparsity and cold start issues.

Keywords: classification; collaborative filtering (CoF); k-means; k-nearest neighbors (K-NN); recommendation; social networks

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1. Introduction

The most widely used uses of big data technology are the recommendation system that effectively addresses the issue of information overload in social networks. However, the model's recommendation quality is affected by the data sparsity issue. This study suggests a hybrid recommendation approach to achieve this. Modern social networking systems make recommendations for friends based on the networks of individual users. This might not be the best technique to advise friends to a particular user because friend suggestions ought to be more heavily weighted toward actual buddy-selecting methods. There are more users who are engaged online than ever before, and social networking sites (SNSs) have taken over as the primary way to make new acquaintances. It has been established that friendships formed through regular physical contact are inferior to those formed through social networking sites (SNS). Each of these social networks relies on a friend recommendation system (FRS), which links individuals together by identifying shared characteristics between them.

It is quite hard to recommend a trustworthy friend to a user with the current social networking systems. The majority of social networking sites currently in use rely on user relationships already in place to suggest peers. A few social networking sites, such as Facebook, rely on social connection analysis between users who already have friends in common. These suggest prospective friends among symmetrical users. According to recent sociological research, people can be divided into a variety of groups based on their attitudes, tastes, lifestyles, and economic status. The everyday activities and habits of a user are strongly tied to their lifestyle. Although it is the most natural characteristic, its utility is limited because it is challenging to observe a user's way of life. If we could gather data on users' everyday activities and routines, and then suggest buddies based on how closely their lifestyles match, that would be a novel approach. This suggestion method can be incorporated into current social networking frameworks or implemented on cell phones as a standalone app. Users of the app can use it to meet friends who lead similar lifestyles to themselves.

Recommender systems (RS) are in higher demand than ever. Recommender systems address the challenge of information overburden [1] by selectively filtering important fragments of information from a huge quantity of dynamically produced data based on user interests, preferences, or observed behaviors [2]. The RS can suggest that the user like an item or consider any user profile. RS benefits service providers and users as well [3]. It decreases the costs of searching as well as selecting items in a typical online purchasing environment [4]. RS has proved to enhance the decision-making process along with quality [5]. RS increases the income of an e-commerce scenario as they effectively sell more products [6]. Collaborative filtering (CoF) requires the users' previous preferences on a set of objects [7]. Based on the legacy data, the CoF adopts the concept that the previously agreed customers do agree again in the future. Concerning user preferences, there are two types. An explicit rating is a numerical rating provided by a user to an item, such as five stars for a Spiderman movie. It is a straightforward way for users to express how much users enjoy a product. RS possess attentiveness in the previous decade because of its powerful capacity to solve information overload [8–10]. The user preferences for certain interests are predicted automatically by the recommender systems, which then supply them with useful recommendations.

People frequently rely on suggestions from friends as well as acquaintances for decisions. Collaborative filtering (CoF) is the most popular recommendation technique to compare neighbors to create multiple suggestions and not differentiate between neighborhood friends and strangers with similar likes. These days, interactions and knowledge exchange on social network websites are the primary means of communication among individuals. Users are unable to acquire suitable information because of the exponential proliferation of data, prompting researchers to investigate social-based recommender systems. The proposed research work concentrates on suggesting friends on social networks. The suggested method begins by supplementing the CoF recommendations with social data. To deal with the rating of variability and sparsity challenges, the social dimension is featured by social behavior measures, namely friendship, trust, and degrees of commitment amongst users. Lastly, social similarity and collaborative measures are employed to improve the accomplishment of the RS classification techniques.

Motivation of Research

Collaborative filtering, as well as content-based semantic models, were the two commonly used algorithms in the prior stages of the creation of RS, which have advanced significantly over the past 10 years. In light of the extraordinary successes of deep learning

(DL) technology in numerous applications of artificial intelligence (AI), the deep learning-based recommendation model has steadily emerged as the focus of researchers' attention. Although the limitations of text mining and user behavior analysis have prevented much progress in these areas of research, they hold great promise for addressing issues with recommendations. In contrast to the classic recommendation algorithm, social networks typically have more severe data sparse and cold start issues, which presents significant hurdles for the study of social recommendation algorithms. This proposed work suggests a hybrid collaborative filtering model based on the aforementioned studies.

Existing research demonstrates that since users' preferences are similar to or influenced by their connected peers, social information can produce more accurate and individualized recommendation outcomes. The semantic features also enable a more accurate depiction of knowledge. However, only a small number of works combined the CoF algorithm with social and semantic data. Some of the current trust-aware recommendation methods primarily rely on trust propagation or the trust-based neighbors of users to find user communities. However, it is important to note that user trust information is not frequently available on social networks. Therefore, we believe that formalizing and modeling the trust for a specific user in the context of a social network while taking into consideration his/her interactions with other users is more pertinent.

Our contributions to this study are mentioned below:

- The proposed recommendation system of users incorporates both social and collaborative classification approaches;
- The proposed study proposes a list of the most acceptable potential friends based on the user's profile;
- The proposed work provides a better RS based on hybridizations of collaborative, semantic, and social filtering;
- The amalgamation of semantic as well as social information completely eliminates the problem of a cold start.

The article is further structured as follows: Section 2 outlines the relevance of the social recommendation research. The recommendation strategy is presented in Section 3. Section 4 provides an outline of the implemented research. Finally, Section 5 details the observations, conclusions, and future scope.

2. Related Works

This section details the fundamentals of social and friend recommendation in a social network. The social recommendation survey reveals the available ways to provide customized recommendations to users by incorporating social network information into CoF. The authors Liu and Lee [11] presented improvement in suggestion efficacy by gathering information from social networks based on preference ratings of users as well as social network affiliations. They examined the CoF performance with a variety of neighborhood groups of friends and nearest neighbors. Their findings showed that adding social network information into CoF can result in more accurate prediction algorithms. Chang and Chu [12] suggested a recommendation algorithm that analyzes information from social networks and estimates user similarity and trustworthiness. The recommender system built an information system for tourism attractions to validate their strategy. Furthermore, the authors analyzed the system through multiple tests by demonstrating more practicable and effective findings.

Banati et al. [13] presented two similarity measures to investigate the influence of explicit social interactions. The foremost metric considers social behavior and assesses user similarity based on "how similar the users are concerning social interaction". The second metric combines the social similarity of two users with their shared interests. They employed a trust-aware SFLA-based CoF recommender system to test the usefulness of the proposed metrics. The designed CoF system utilizes the social behavior measurements that performed better than hybrid CoF and conventional CoF systems for a small set of target users experimented on Epinions datasets. However, according to the authors, the hybrid approach takes over and delivers superior recommendations as the rate of active users rises. Su et al. [14] suggested a recommender system of music that predicts users' preferences by combining social and collaborative information. According to the authors, user preferences are deduced accurately and effectively by utilizing integrated social and collaborative information. Experimental results show a reduction in issues with better results.

Few studies employed classification approaches to increase social recommendation performance [15]. Najafabadi et al. [16] attempted to increase the CoF recommendation accuracy by using a public dataset. The authors experimented with and compared the findings of basic CoF and expanded versions of CoF approaches, such as K-means clustering and probabilistic learning. Even when the data are sparse, the experimental results show that their technique outperforms basic CoF and other expanded variants of CoF algorithms in terms of accuracy and recall.

Agarwal et al. [17] observed the scoring matrix based on CoF and user social relationships. Their work adjusted the ranking based on the users' natural feature information and the intensity of their interactions. Tang et al. [18] introduced a model to calculate user interest similarity to improve recommendation accuracy. Zhang et al. [19] suggested a hybrid RS model based on social relations as well as time-sequenced themes. Li YM et al. [20] suggested an RS based on similarity preference, trust of recommendation, and social interactions to generate tailored product recommendations. By including social network information in CoF, Liu and Lee [20–22] showed improvement in suggestion efficacy. To create the suggestions, Wang and Huang [21] combined the friendships, but they did not distinguish between the different connections between the individuals.

Few efforts observed on social recommendation have added new ideas such as physical proximity, the popularity of items, and point of interest. Chen et al. [22] created an RS based on the preferences in addition to the attention of users. Lai et al. [23] suggested a method for predicting user preferences by recommending suitable products in social networks using a social recommendation mechanism by combining interactions, trust relationships, and product popularity. The comprehensive survey of different recommendation systems proposed recently is shown in Table 1.

Table 1. Comprehensive survey of recommendation systems.

Sl. No.	Study and Year	Techniques	Remarks
1	Zhang, Z et al. (2015) [24]	This approach is based on the law of entire probability and leverages the total characteristics information provided by the user.	The effectiveness of each of these friend referral techniques may vary depending on the quantity of users' current friends. The performance of Adamic/Adar is inferior, and Jaccard's coefficient may be unacceptably high when the number of existing friends is fewer than 100.
2	Anuja Shahane et al. (2016) [25]	The friend-matching graph is suggested as a measure of similarity.	Recommendations are made only based on users' lifestyles that are comparable.
3	H. Zheng and J. Wu (2017) [26]	A user is provided recommendations for k new acquaintances so that the user might increase his or her social impact through new friends.	Users' semantic relationships were not taken into account.
4	Sanjeev Dhawan et al. (2018) [27]	There were offered recommendations based on both content and location.	All the users' attributes and semantic information were not considered.

Table 1. *Cont.*

Sl. No.	Study and Year	Techniques	Remarks
5	Srikantaiah K C et al. (2020) [28]	KNN algorithm was used for the recommendation. User preferences are taken for similarity measures.	As a result, the suggested technique only considers the nearest point based on an iterative selection process utilizing a distance vector, rather than considering all nearby points simultaneously in order to bundle a single point.
6	Ruksar Parveen and N. Sandeep Varma (2021) [29]	Similarity cosine and Jaccard distances are used to calculate coefficients. Page rank is used to calculate ranking metrics.	Semantic association was not taken into account.
7	Roy D and Dutta, M (2022) [30]	The effectiveness of recommender systems cannot be determined using a common metric. In 60 studies, system performance was calculated using 21 recall, 10 MAE, 25 precision, 18 F1 measure, 19 accuracy, and only 7 RMSE.	The authors only examined studies that had been published in management, computer science, and medical journals. Second, they looked at only English-language papers.
8	Zhu et al. (2019) [31]	To evaluate the performance of trust-based recommendation method, experiments are conducted on real LBSN datasets. The experiment results show that compared with the existing friend and POI recommendation algorithms, trust co-cluster-based friend recommendation algorithm and hybrid POI recommendation algorithm are more accurate and time efficient.	The authors have to include semantic information in the clustering process to further improve the quality of friend and location recommendations.
9	J. Zhu et al. (2017) [32]	Results on Twitter and RayLeague demonstrate that their method can effectively address the influence maximization problem and increase not only the influential range but also time efficiency when compared to existing algorithms.	Social networks are constantly being updated, causing nodes' structural characteristics to change. In order to scale our technique to large-scale dynamic networks, the authors must expand their influence maximization algorithm based on structure hole theory.

3. Materials and Methods

This section details the proposed enhancement of the CoF algorithm that incorporates collaborative and social data into the recommendation process.

3.1. Combination of Social and Semantic Filtering

Figure 1 shows the different components of the profile of user. The combination of social-based CoF and semantic approach is shown in Figure 2.

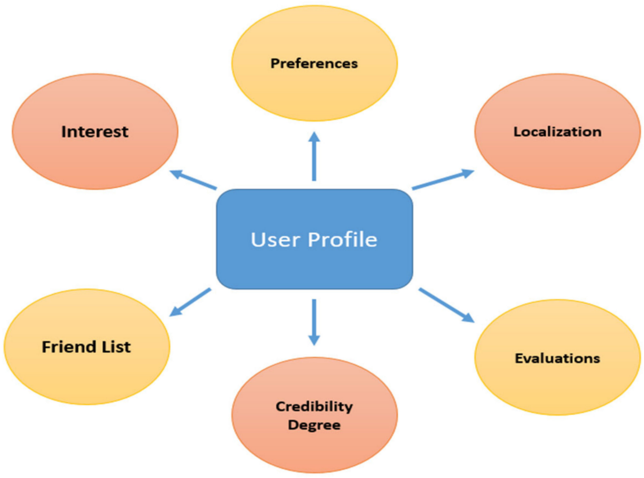


Figure 1. The components of user's profile.

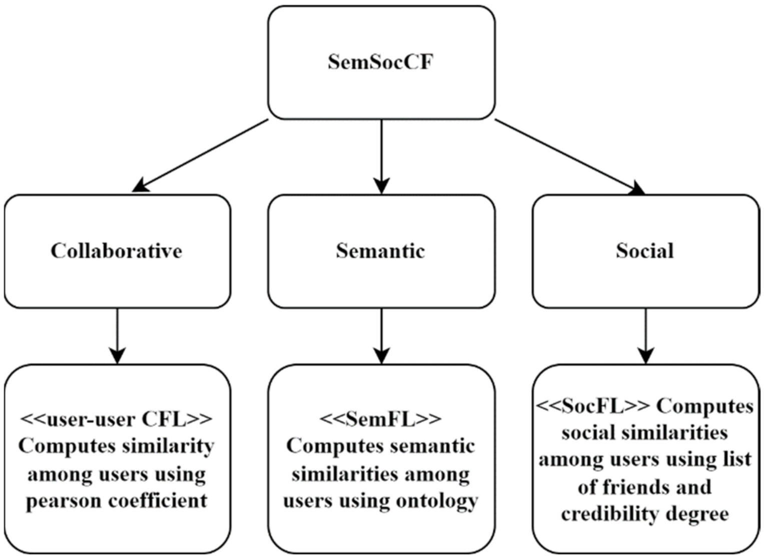


Figure 2. The combination of social-based CoF and semantic approach.

The semantic filtering (SemF) algorithm being used to compute the similarity degree among the user and other remaining users; suggests the users with a certain threshold of similarity degree.

(1). CoF based on user–user

A memory-based CoF technique and user-to-user recommendation system are employed in the current research work. The proposed approach uses the utilization matrix to determine which neighbors are best for a user [33]. The ratings by the users are utilized to create the rating matrix. The Pearson correlation formula determines the degree of similarity between users. Pearson correlation is a measure of linear relationship strength and direction. This metric is calculated for the vectors P and Q, as shown in Equation (1). Essentially, the calculation involves the division of covariance by-product of the standard deviations. Users' collaborative similarities allow for the identification of neighborhoods.

$$CORR(P,Q) = \frac{\sum_{i=1}^{n} (P_i - \overline{P})(Q_i - \overline{Q})}{\sqrt{\sum_{i=1}^{n} (P_i - \overline{P})^2}\sqrt{\sum_{i=1}^{n} (Q_i - \overline{Q})^2}} \quad (1)$$

where $\overline{P} = \frac{1}{n}\sum\limits_{i=1}^{n} P_i$

(2). Social Filtering (SocF)

User profile social information is calculated using two metrics such as friendship and credibility [34]. Commitment and trust degree are two characteristics used to determine an active user's credibility.

Friendship metric: As shown in Equation (2), this metric calculates the similarity weight among two users, *user1* and *user2*, based on the social links of users, described as the size of the intersection by the size of union.

$$Sim_{Social}(user_1, user_2) = \frac{size(F(user_1) \cap F(user_2))}{size(F(user_1) \cup F(user_2))} \tag{2}$$

where $F(user_1)$ and $F(user_2)$ depicts friends of $user_1$ and $user_2$, respectively.

Multiple methods exist to evaluate the resemblance among 'n' components. Using the formulation in Equation (3), recommendation systems may suggest components very close to the user's current pattern.

$$Similarity = \sum_{i,j=1}^{n} (user_i \cdot user_j) / \sqrt{\sum_{i=1}^{n} user_i^2} \cdot \sqrt{\sum_{j=1}^{n} user_j^2} \tag{3}$$

Degree of commitment metric: To calculate the degree of commitment, two characteristics are considered. Firstly, an active user involvement level that includes the number and type of evaluations completed by the user. Secondly, user sociability level that represents the social network friendship rate. The degree of commitment is computed using Equation (4).

$$Degree\ Of\ Commitment(user) = \theta_1 \cdot Participation(user) + \delta_1 \cdot Sociability(user) \tag{4}$$

where θ_1 and δ_1 are weights that express level of priority with $\theta_1 + \delta_1 = 1$.

User participation degree: Specifically, it refers to the number of user-performed evaluations. This is being generated based on the total count of evaluations completed by the user, $NumEval(user)$, in relation to all of the system's evaluations, $NumTotalEval$. It is computed using Equation (5).

$$Participation(user) = \frac{NumEval(user)}{NumTotalEval} \tag{5}$$

User sociability degree: This degree is determined by the number of friends a user has among all of the social network's registered users, as shown in Equation (6).

$$Sociability(user) = \frac{NumFriends(user)}{NumUsers - 1} \tag{6}$$

Degree of trust metric: This metric uses the following formula to take into account user's seniority and level of skill in the social network, as shown in Equation (7).

$$Degree\ Of\ Trust(user) = \theta_2 \cdot Seniority(user) + \delta_2 \cdot Competency(user) \tag{7}$$

where θ_2 and δ_2 are weights that express level of priority with $\theta_2 + \delta_2 = 1$.

- User's seniority level is computed as shown in Equation (8) using the date of the user's social network registration [34];

$$Seniority(user) = \frac{Current\ Date - Registration\ Date\ of\ user}{Current\ Date - Social\ networking\ Starting\ Date} \tag{8}$$

- User's competence level: It is estimated in two steps, based on the presumption [35] that "a friend is very competent if only if the friend has accurately evaluated all the resources in comparison to his mean ratings in social networks".

  The steps involved are as follows:

Step 1: Compute a friend F's competency level in relation to a specific item R_j. We begin by determining the mean of each item's evaluations [35]. The mean value is then compared with the F's rating given for the identical item, as shown in Equation (9).

$$Competency(F, R_j) = \begin{cases} \frac{mean(R_j)}{Eval_{i,j}} & if\ Mean(R_j) \leq Eval_{i,j} \\ \frac{Eval_{i,j}}{mean(R_j)} & if\ Eval_{i,j} \leq Mean(R_j) \end{cases} \quad (9)$$

where $mean(R_j)$ is the item's mean rating based on the opinions of all users, and $Eval_{i,j}$ is the evaluation of F for the item R_j.

The competency degree at the global level for the friend is computed using Equation (10) below:

$$Competance(F) = \frac{1}{n} \sum_{i=1}^{n} Competency(F, R_j) \quad (10)$$

where n denotes the total amount of items evaluated by friend.

Step 2: Compute the friend's global trust level using the following formula, as shown in Equation (11):

$$Trust(F) = \frac{1}{num} \sum_{j=1}^{num} Degree_{Competency}(F,\ R_j) \quad (11)$$

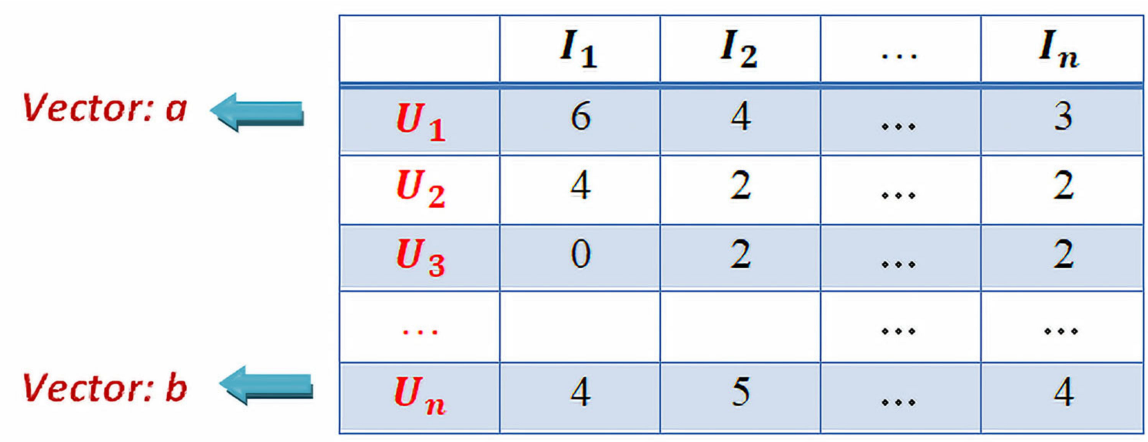
where num is the total count of items that the friend has evaluated.

(3). Semantic Filtering (SemF):

Any information-filtering technique used to examine the textual content of social networks and combat information overload must deal with two challenges. Firstly, the absence of context, and secondly, a dynamically changing language [36]. Analyzing social network textual contents is very critical to the development of an efficient information-filtering system. However, it is essential to determine the user interests based on posts liked or posts shared over social media and filter posts relevant to user interests. Natural disasters, elections, and sporting events may all be tracked via social media. Changes in the dictionary that are being used over social media mirror changes in these themes [37]. During natural disasters, social network interactions alter dramatically over time. As the crisis progresses, the disasters have been proven to move through phases [38].

If the degree of closeness between two users, user1 and user2, is more than or equal to a particular threshold, they are denoted as semantically close friends. This indicates that general resemblance will be calculated based on several characteristics. The user–user CoF approach is depicted in Figure 3. Consider the following parameters,

Sharing of knowledge domains of similar users
Sharing of preferences of users that are similar



	I_1	I_2	...	I_n
U_1	6	4	...	3
U_2	4	2	...	2
U_3	0	2	...	2
...			...	...
U_n	4	5	...	4

Figure 3. An example of user–user CFL method.

Computation of similarity between two users is shown in Figure 4.

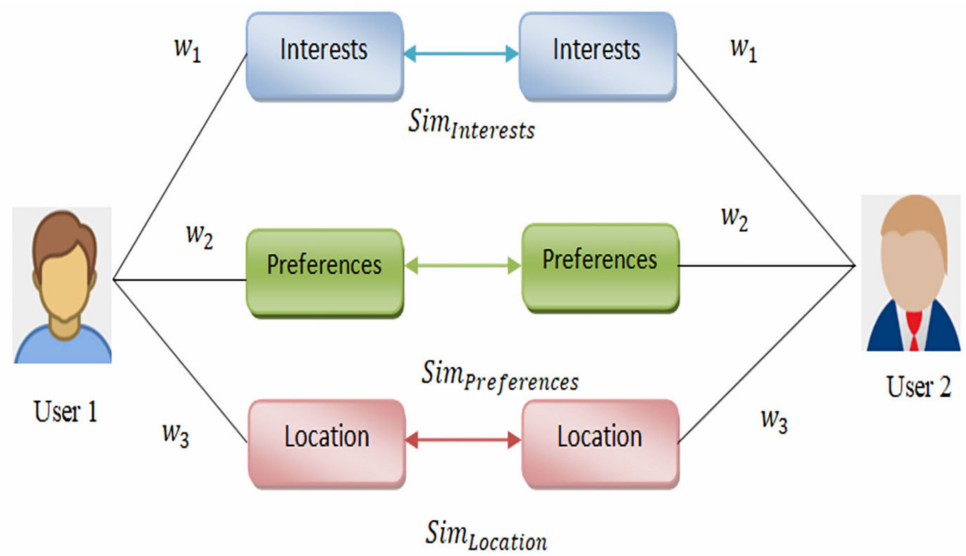


Figure 4. Computation of similarity between two users.

The global similarity is computed using the formula [39], as shown in Equation (12).

$$Sim_{Global}(user_1, user_2) = \frac{\sum_{i=1}^{NP} Sim_i(user_1, user_2) * w_i}{NP} \tag{12}$$

where NP is partial similarities number; $Sim_i(user_1, user_2)$ is partial similarity and w_i denotes weights representing priority level.

$Sim_{Interests}$ (interests-based similarity): Calculates the similarity degree among active user 1 and all the remaining users in terms of their knowledge domain, utilizing DKOnto, that is, domain knowledge ontology, which represents the ideas connected to the interested domain. Figure 5 depicts a portion of this ontology.

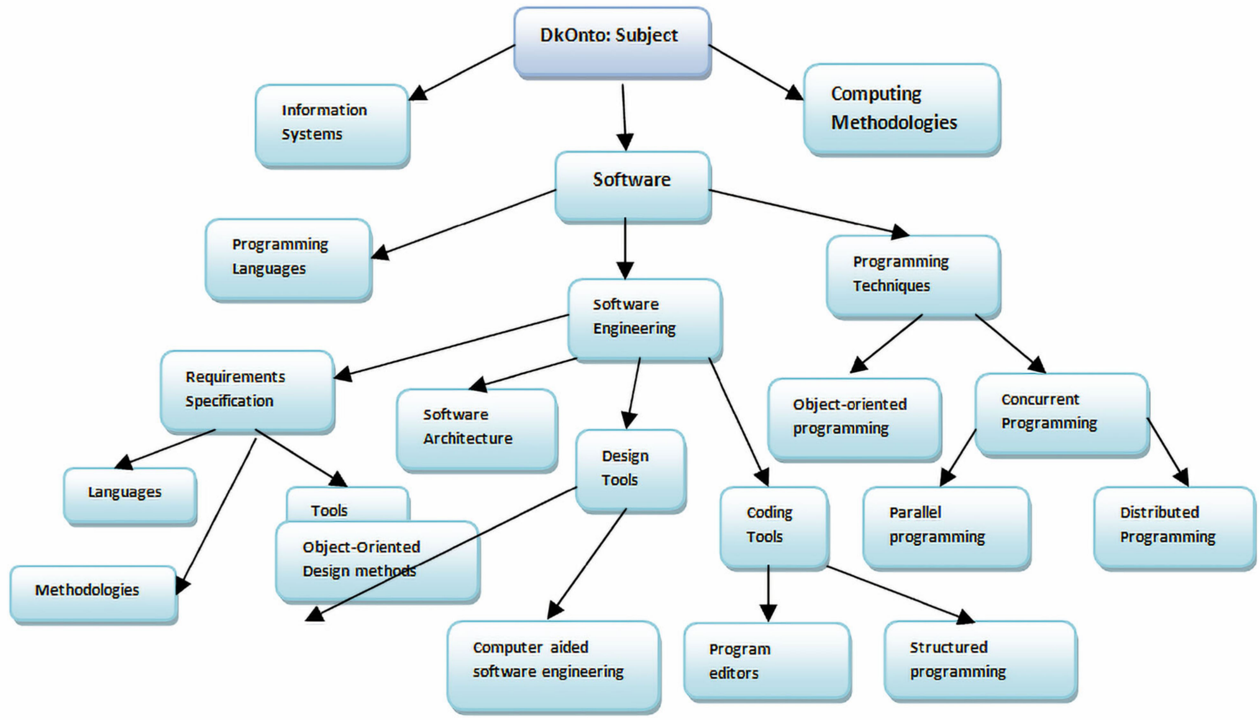


Figure 5. A portion of computer-science domain ontology.

User 1, as well as his friend user 2, may have multiple areas of interest. A similarity matrix is being created in which the lines show all of user 1′s domains D, and the columns represent all of user 2′s domains $D^|$.The similarity measure of Wu et al. [40] is used to compute the matrix elements, as shown in Equation (13).

$$Sim\left(D, D^|\right) = \frac{2 * Depth(D_c)}{Depth(D) + Depth\left(D^|\right)} \quad (13)$$

where D is the domain of user 1 and $D^|$ is the domain of user 2. Depth (D) is D′s depth, $Depth\left(D^|\right)$ is $D^|\prime s$ depth, and D_c is the nearest familiar parent to both D and $D^|\prime$.

Using the similarity measure specified in [41,42], let us investigate the similarity among two domains, namely 1. "*Tools*" and 2. "*Software architecture*", as shown in Equations (14) and (15).

$$Sim(Tools,\ Software\ architecture) = \frac{2 * Depth(software\_engineering)}{Depth(Tools) + Depth(Software_{architecture})} = \frac{2 * (3)}{(5) + (4)} = 0.66 \quad (14)$$

Finally, the mean of matrix elements is calculated to produce a global similarity:

$$Sim_{interests}(user_1, user_2) = \frac{1}{N} \sum_{i=1}^{M} Simi\left(D_i, D_j\right), j = 1 \ldots N \quad (15)$$

$Sim_{Preferences}$ (preferences-based similarity): the attributes of the user's most evaluated items are referred to as preferences. A couple represents each preference (preference name: count of reviews carried). It is computed using Equation (16).

$$Preferences(user) = (a, n)|n > 0 \quad (16)$$

where a is the attribute and n is total amount of rating made by user for attribute a.

The Jaccard index used to calculate the similarity preferences of two users is shown in Equation (17).

$$Sim_{Preferences}(user_1, user_2) = 1 - \frac{\sum_{a \in A} \min(n_a, m_a)}{\sum_{a \in A} \max(n_a, m_a)} \quad (17)$$

where A is the set of all preferences of user 1 and user 2, n_a is count of reviews performed by $user_1$ on attribute a, and m_a is count of reviews performed by $user_2$ on attribute a.

$Sim_{Location}$ (geographic location-based similarity): The data based on geography reflect a user's spatial attributes. The objects' locations that the user has examined are taken into account so as to determine where the user spends the most time. The following Equation (18) is a description of the information:

$$Locations(user) = \{\ (latitude,\ longitude, num)|num > 0\} \tag{18}$$

where *num* is the total count of reviews of the item that the user *has* performed.

3.2. Combination of Classification Algorithms with Social-Based Collaborative Filtering (SoC-CoF)

The classification of the recommendation approach has the primary goal of grouping comparable individuals based on social dimensions. It reduces the duration of time needed to find neighbors and thereby allows grouping together the different groups. As a result, each social network user has both collaborative as well as social class. Furthermore, if a user has buddy friends, but has not yet completed enough evaluations, the system suggests other friends solely based on the social component. In the same way, if user has completed enough evaluations and is still yet to add any friends, the system will suggest new friends completely based on the collaborative dimension.

(1). Incremental K-means

A variation of K-means, namely, incremental K-means, was used, which was described in [43]. The initialization problem of centroids is no longer a problem with this technique. This is based upon the global K-means approach, which seeks to reach an ideal solution, rather than having a single population center (global K-means). This method selects two objects, each of which is the middle point of cluster, with the latter two being the farthest apart. The next stage is to select the next middle point or center. Distance among the cluster's center, as well as its neighbors, can be calculated using a simple function. The elected contender for the new centroids is the furthest element of the center. Following this, clusters are reassembled by impacting the collection of items with the shortest distance between them and the center. This process is repeated until a total of K clusters have been formed.

(2). K-NN algorithm

This approach has a complexity of O (num), where num is the total count of users in training set. Since this method is time-consuming, the newly issued ratings cannot be used to swiftly update the categorization acquired by the algorithm incremental K-means. To overcome this barrier, we applied both collaborative as well as social K-NN methods, which were tuned for collaborative and social categorization, respectively.

3.3. Proposed Algorithms for HCoF Recommendation Systems

We performed certain preprocessing activities for the incorporation of data that are implicit before accessing the Yelp database. The resulting database contains 4823 restaurants, and 5436 individuals who rated these restaurants 118,709 times in 65 categories (only users who rated more than 9 restaurants are considered). The SocCoF user recommendation as shown in Algorithm 1 incorporates both social as well as collaborative classification approaches.

Algorithm 1 SocCoF recommendation.

Input required: User Table containing Collaborative and also, users' social classes
Output expected: Recommended Friends list of user "u".
Step_1: Let α *represents a weighted level of Collaborative Class(CClass) and* β *as social class(SClass)*
Step_2: if u has CClass and SClass then $\alpha = 0.5$ *and* $\beta = 0.5$
if u has no CClass and kas SClass then $\alpha = 0$ *and* $\beta = 1$
if u has CClass and has no SClass then $\alpha = 1$ *and* $\beta = 0$
if u has no CClass and no SClass then $\alpha = 0$ *and* $\beta = 0$
Step_3: if u has no CClass and no SClass then
Add Recommended list to very active users of social network.
Step_4: For the remaining users namely $u^{|}$ *not friends of who has same CClass and SClass:*
Calculate credibility: Take 80% of Trust, 20% of Commitment
Recommend_val: 80% of CClass and SClass and 20% credibility of user
If Recommend_val > threshold value, add $u^{|}$ *to the recommended list of user u*
Step_5: Repeat 2 to 4 for all the users present in user table

The subsequent recommendation algorithm proposes a list of quite commonly acceptable potential friends based on the user's profile. As follows, we offer the semantic as well as social-based CoF (SemSocCoF) recommendation algorithm, as shown in Algorithm 2.

Algorithm 2 SemSocCoF recommendation.

Input required: Profile of user and rating matrix
Output expected: Recommended Friends list of user "u".
Step_1: if user "u" is actually a new user of the social network, then add him to the active users of social network.
Step_2: if not step 1 and if the user "u" does not have enough rating, combine the Semantic Filtering (SemFL) and the Social filtering (SocFL) values.
Step_3:if step 2 is not satisfied, then combine collaborative filtering values with the Semantic Filtering and the Social filtering values.
Step_4: Display the Recommended List in sorted order

The SocFL method will be used if the user u has friends, but his profile is not properly informed. Similarly, the SemFL algorithm will be used if the user u has an informed profile (a preference and/or interest list is available), but has not yet added any friends. On the other side, if there are sufficient evaluations, the SemSocCoF algorithm, which combines the CoF algorithm with the semantic and social algorithms, will be used (i.e., in this case, the CoF is applicable). The following combinations of the three algorithms were taken into consideration (CoF, SemFL, and SocFL).

- The Sem-based CoF and the Soc-based CoF were created to examine the influence of semantics and social information, respectively, on the CoF suggestions. For the Sem-based CF algorithm, the neighborhood computation in the CoF will be based on the list of semantically close friends, and for the Soc-based CoF method, it will be based on the list of socially close friends;
- Semantics and social information are used in the Sem-Soc-based CoF to examine its impact. In this instance, the list of semantically and socially close friends will serve as the foundation for the neighborhood computation in the CoF.

Out of 5436, 2400 users are categorized as new users, 1924 users are observed to be existing users with minimal ratings, and thus 1112 users are identified to be evaluated under step 3, which combines collaborative filtering with semantic filtering and the SocialSem filtering process. Since the SemSocCoF testing range (u = 1112) is lesser than the testing range of other two categories, we assessed the SemSocCoF process with the same range of other two categories (i.e., for all three recommendation process common and minimal testing range (1112) is considered. Though a uniform testing range is fixed, it is necessary to verify the diversity of the user, which can be estimated via fairness equalized odds process.

Equalized odds assess whether the recommendation system is equally accurate for users from different diverse groups. It is calculated as follows:

$$P(\alpha) = P(\beta) \tag{19}$$

where, α = (true outcome | diverse user group, recommendation), β = (true outcome | diverse user group).

From Equation (19), the probability of accurately predicting the true outcome (such as a user liking an item) given a particular diverse user group and a recommended item should be the same as the probability of accurately predicting the true outcome for that diverse user group overall. If the recommendation system is biased towards one diverse group, then the left-hand side of the equation will be higher or lower than the right-hand side.

The above fairness for step 3 process can be delineated with a perfect example. Let us say we randomly select 100 "u" ratings to evaluate the recommendation system's accuracy. We find that for users under age group 30, the recommendation system accurately predicts the true rating for 60% of the ratings, while for users over 30, it accurately predicts the true rating for 70% of the ratings.

Using the equalized odds equation, we can assess whether the recommendation system is equally accurate for both age groups:

P(predicted rating = true rating | under 30, recommendation) = 0.6 P(predicted rating = true rating | over 30, recommendation) = 0.7 P(predicted rating = true rating | under 30) = 0.55 P(predicted rating = true rating | over 30) = 0.6

We can see that the left-hand side of the equation is higher for users over 30 than for users under 30, which suggests that the recommendation system is more accurate for users over 30. However, the right-hand side of the equation is also higher for users over 30 than for users under 30, which suggests that users over 30 are generally easier to predict accurately.

From Figure 6, it is noted that for the balanced user (u = 1112) level, a precise accuracy is obtained for the overall trial estimation of each methodology. Evidently, the outcome exhibits that the combination of SemSocCoF algorithm yields better results (96.49%) than the other methodologies. In addition to these outcomes, though there is slight decrease in the accuracy level for unbalanced users, SemSocCoF algorithm still performs better than the other models with more than 90% accuracy level. All the facts state that the recommendation system is fair across diverse users.

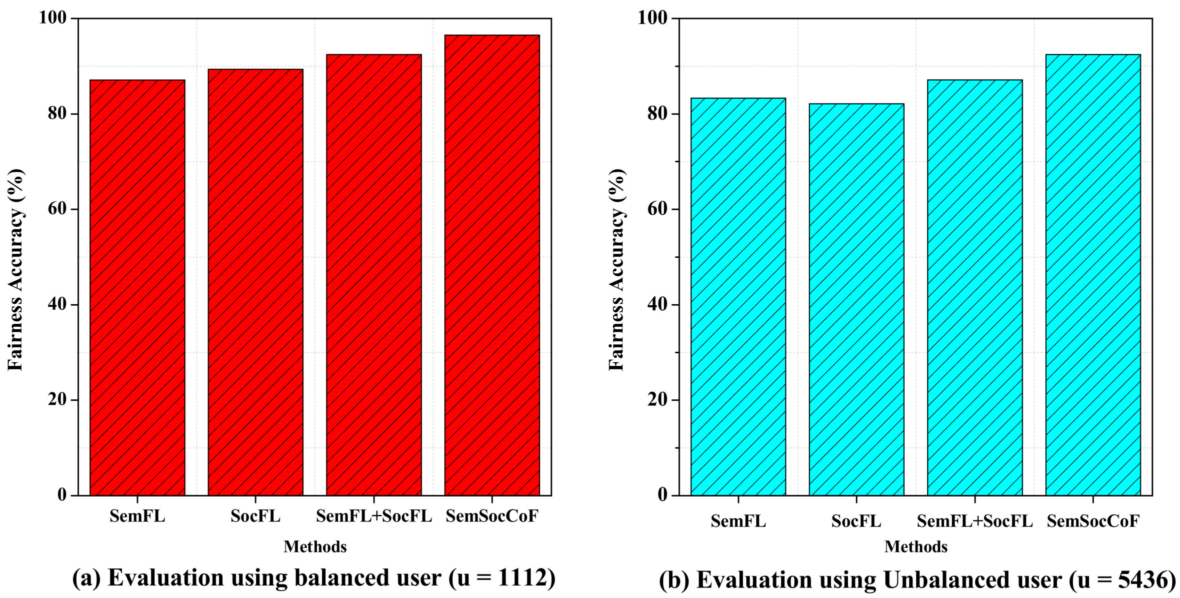


Figure 6. Fairness accuracy.

4. Results and Discussions

We conducted a number of experiments on the Yelp social network, whose primary goal is to link users with nearby businesses, in order to evaluate our methodology. Yelp's "restaurant" category was our selection because it is the most frequently used category on this social media platform. To complete the definition of profiles, we took advantage of the user interaction records. The implicit information of a specific user consists of his or her preferences and interests, the quantity of his or her evaluations and votes (funny, useful, cool), the average number of stars (he or she assigned to the restaurants he or she evaluated), involvement levels, and levels of trust. The total number of reviews a restaurant has received over time and the average number of stars it has received make up implicit information about that restaurant at time t. The analysis of the Yelp database revealed that many restaurants had characteristics that other establishments do not. Only the most popular and pertinent ones were retained, such as "Good For Groups", "Take-out", "Late-night", "Outdoor Seating", "Good for Kids", "Street", "Delivery", "Accepts Credit Cards", "Classy", "Garage", "Romantic", "Expensive", "Wi-Fi", and so on.

The different evaluation metrics, along with evaluation results, are discussed in this section.

A. *Evaluation metrics*

The model developed was evaluated against different performance metrics [40]. The accuracy is calculated using Equation (20).

$$Accuracy = \frac{TNs + TPs}{TNs + TPs + FPs + FNs} \tag{20}$$

where *TPs* are true positives, *TNs* are true negatives, *FPs* are false positives, and *FNs* are false negatives.

The precision is computed using Equation (21).

$$Precision = \frac{TPs}{TPs + FPs} \tag{21}$$

The recall is computed using Equation (22).

$$recall = \frac{TPs}{TPs + FNs} \tag{22}$$

$F1$-score, which is also called harmonic mean, is computed [41], as shown in Equation (23).

$$F1\ Score = 2 * \frac{precision * recall}{precision + recall} \tag{23}$$

B. *Experimental Results*

The CoF using the Pearson correlation function is tested by varying the similarity rate from the values 0.1 to 0.9 (similarity threshold). The Soc-CoF is assessed by altering the three parameter weights, such as commitment, friendship, and trust levels. Consider that $a1$ denotes friendship, $b1$ denotes commitment, and c represents trust. The results of the testing revealed the fact that combining $a1$ = 0.1, $c1$ = 0.3, and $b1$ = 0.6 delivers better results with respect to performance metrics than the other two combinations, as shown in Figure 7.

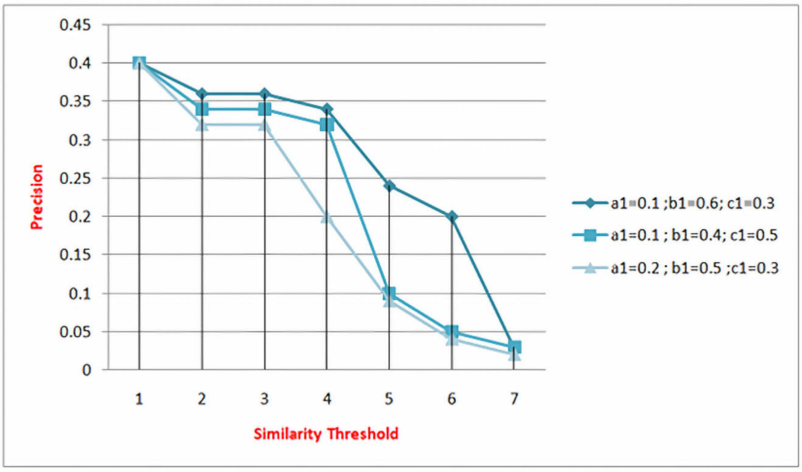


Figure 7. Social parameter weight identification.

The SocCoF was assessed using the optimal parameters for every algorithm. Figure 8 shows how the usage of social data improved the accuracy of CoF recommendations. When compared to the CoF, the SocCoF provided superior precision and F-measure.

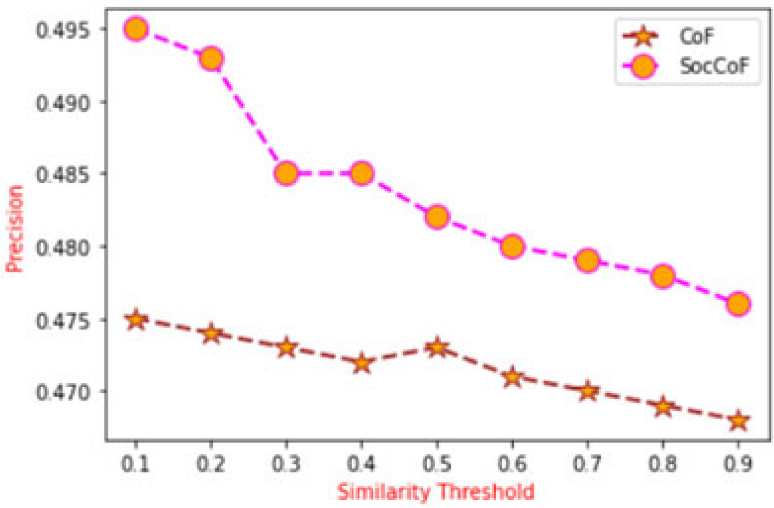


Figure 8. Social information contribution on CoF recommendation.

To compare K-means as well as incremental K-means evolution, the focus is on social classification in this experiment and simulated social network evolution using a database partition with 150 members, 351 restaurants, and 4852 ratings. In the experimental setup, the parameter $K = 3$ identifies the social class numbers, sets the threshold to value 0.3, and experiments with the total count of evaluations (NubE), users (NubU), and destroyed/deleted friendships (NubDF) to see if the system could suggest them again. The results achieved are displayed in Table 2.

Table 2. Outcomes of K-means and incremental K-means algorithms with social information.

NubU	NubE	NubDF	K-Means Precision	K-Means Recall	K-Means F1	Incremental K-Means Precision	Incremental K-Means Recall	Incremental K-Means F1
110	2955	770	0.052	0.090	0.076	0.105	0.040	0.062
120	3263	801	0.124	0.045	0.120	0.120	0.044	0.066
130	3346	813	0.132	0.068	0.160	0.157	0.055	0.081
140	3567	912	0.209	0.040	0.060	0.220	0.061	0.090
150	3770	1006	0.128	0.035	0.045	0.221	0.054	0.081

Figures 9–11 depict the distinction between the progression of the social K-means algorithm as well as the social-incremental K-means algorithm.

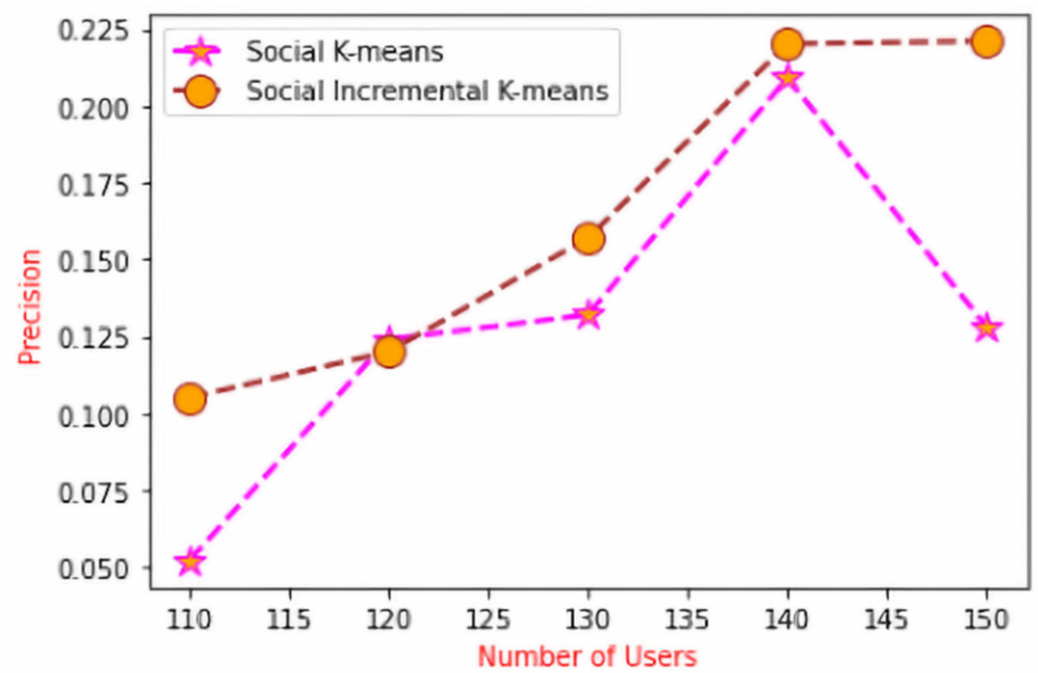


Figure 9. Precision—K-means versus incremental K-means algorithms with social information.

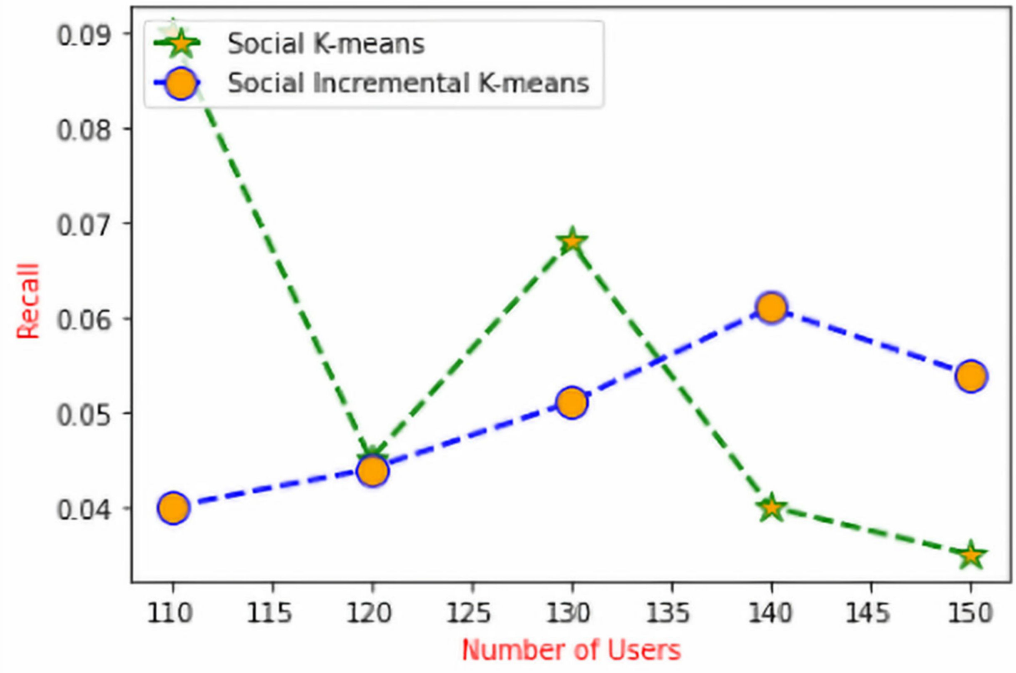


Figure 10. Recall—K-means versus incremental K-means algorithms with social information.

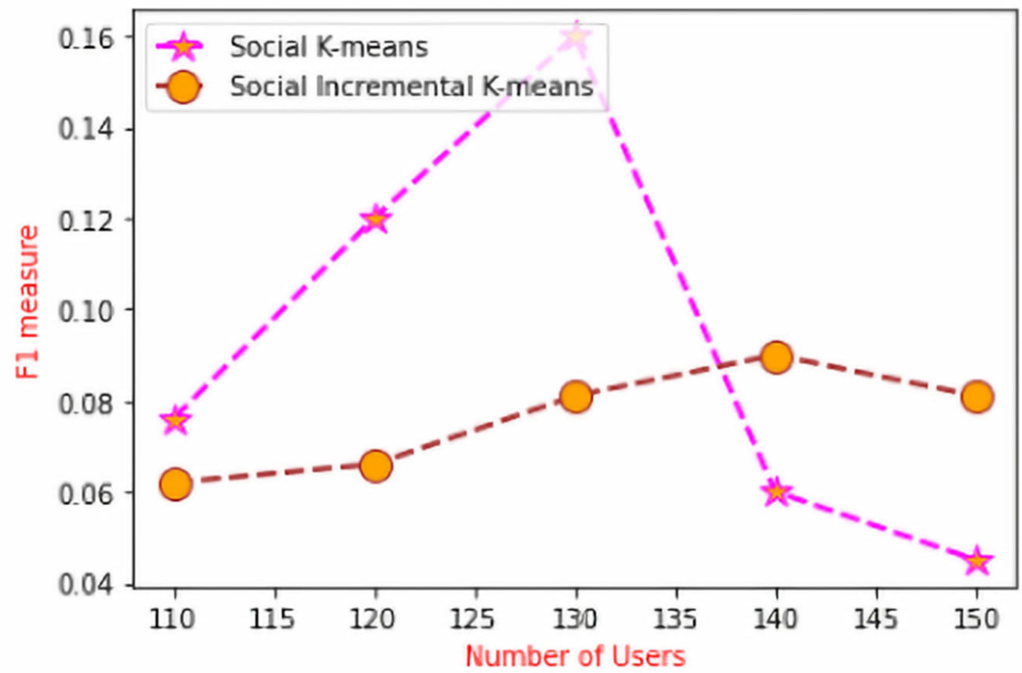


Figure 11. F1 measure—K-means versus incremental K-means algorithms with social information.

The numerous combinations of the SemF, SocCoF, and different amalgamations of the CoF, the SemF, as well as the SocCoF are assessed. The precision and F1 of semantic-based SocCoF and SocCoF algorithms are shown in Figures 12 and 13. The inclusion of semantic information with SocCoF increased the performance of the recommendation model, as evidenced by this evaluation.

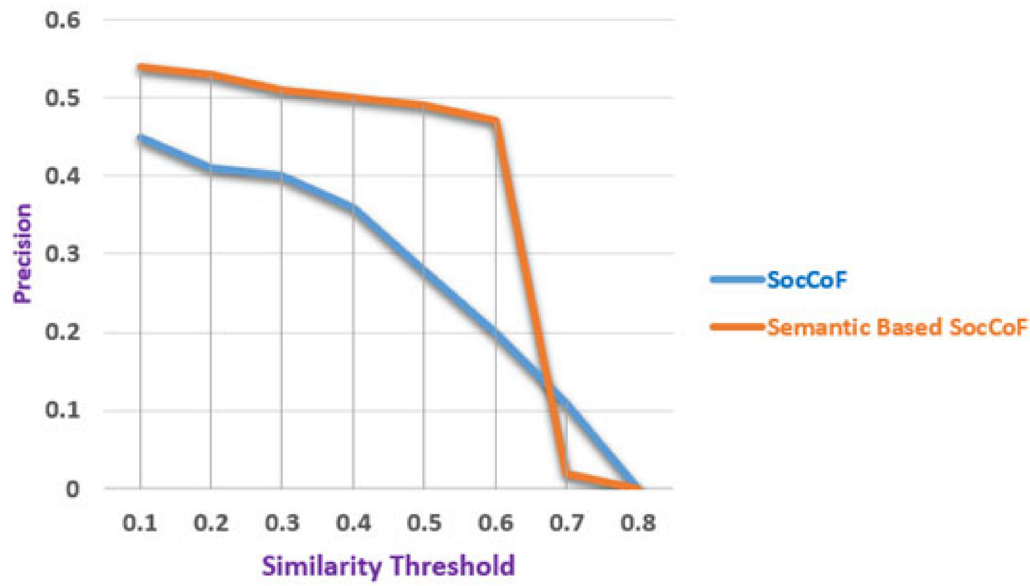


Figure 12. Precision of semantic-based SocCoF and SocCoF algorithms.

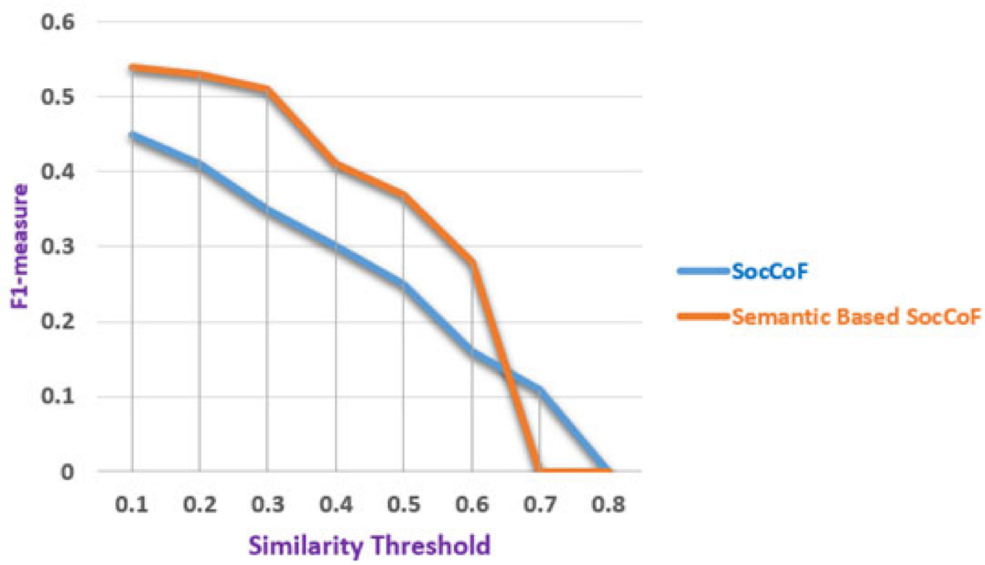


Figure 13. F1 measure of semantic-based SocCoF and SocCoF algorithms.

When compared to the CoF and other algorithms, the SemSocCoF performs better. As seen in Table 3, combining semantics with social information improved the correctness of CoF recommendations. The mean precision, mean recall, and mean F-measure of various techniques are presented. In comparison to the classic CoF method, the findings highlight the hybrid approach's contribution.

Table 3. Summary of the results obtained by different algorithms.

Algorithm/Metric	CoF	SemCoF	SocCoF	Semantic-Based SocCoF	Social-Based SemF	SemSocCoF
Mean Precision	0.430	0.170	0.200	0.334	0.330	**0.503**
Mean Recall	0.180	0.315	0.310	0.424	0.366	**0.892**
Mean F1	0.610	0.225	0.241	0.376	0.351	**0.651**

Figures 14 and 15 show the performance metric values of the various methods by adjusting the similarity threshold value for each algorithm from 0.1 to 0.9.

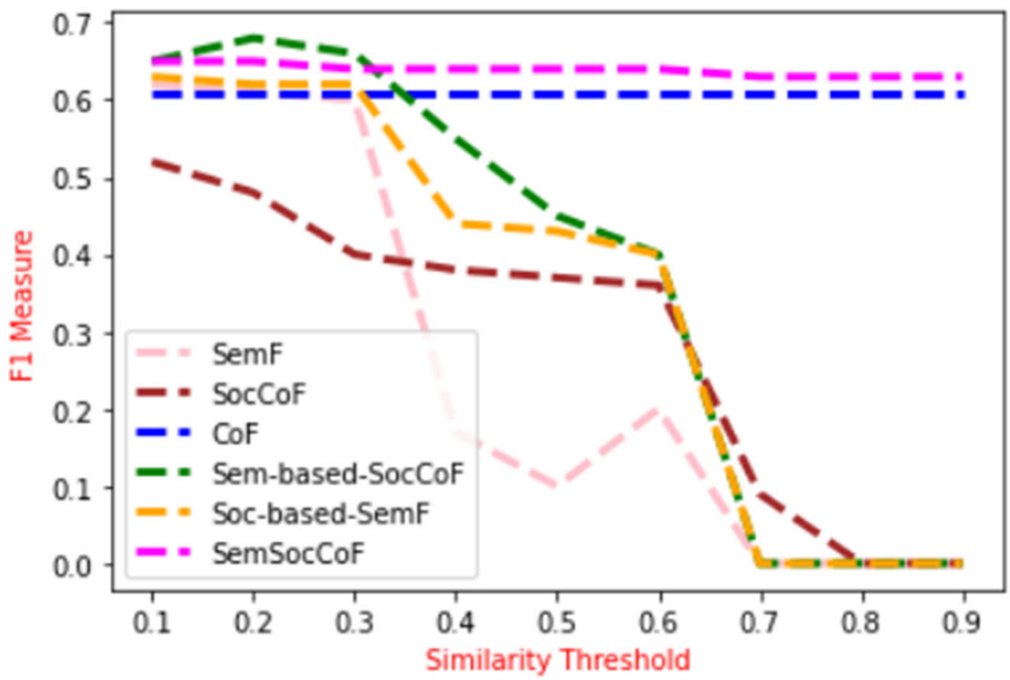


Figure 14. Comparison of F1 measure of various algorithms.

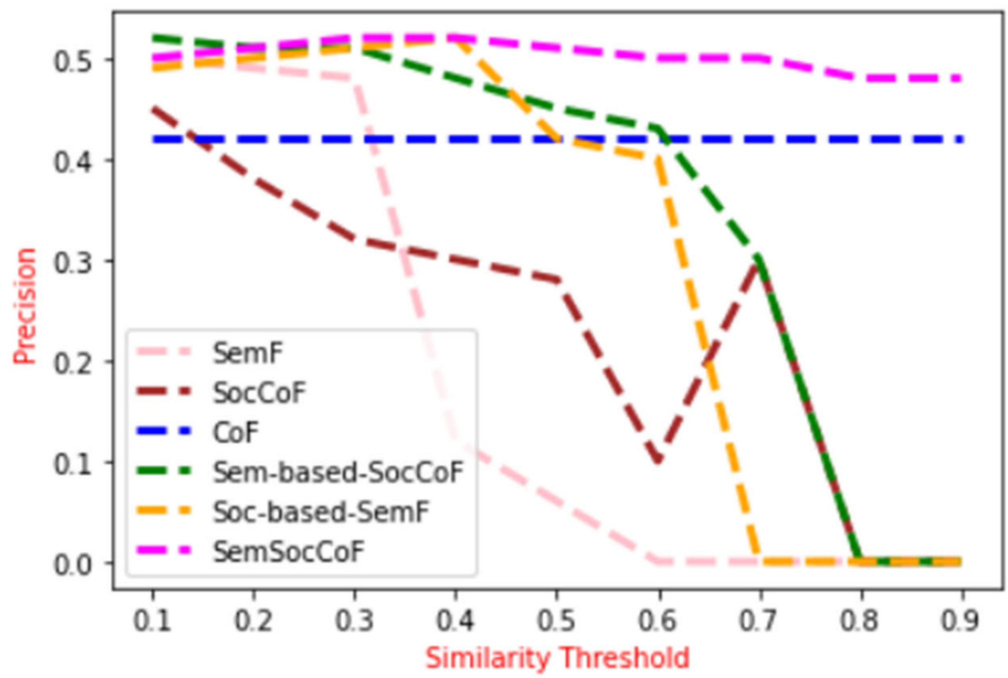


Figure 15. Comparison of precision values of various algorithms.

The hybrid SemSocCoF algorithm is tested using three different combinations: (1) amalgamation of the CoF, the SemF, and the SocCoF based solely on friendship factor; (2) combining the CoF, the SemF, as well as the SocCoF based solely on trust; and (3) combining the CoF, the SemF, and the SocCoF based on both friendship and credibility factors. In comparison to the other algorithms, the SemSocCoF approach showcased the best results compared to all the performance metrics. The result with respect to precision is shown in Figure 16.

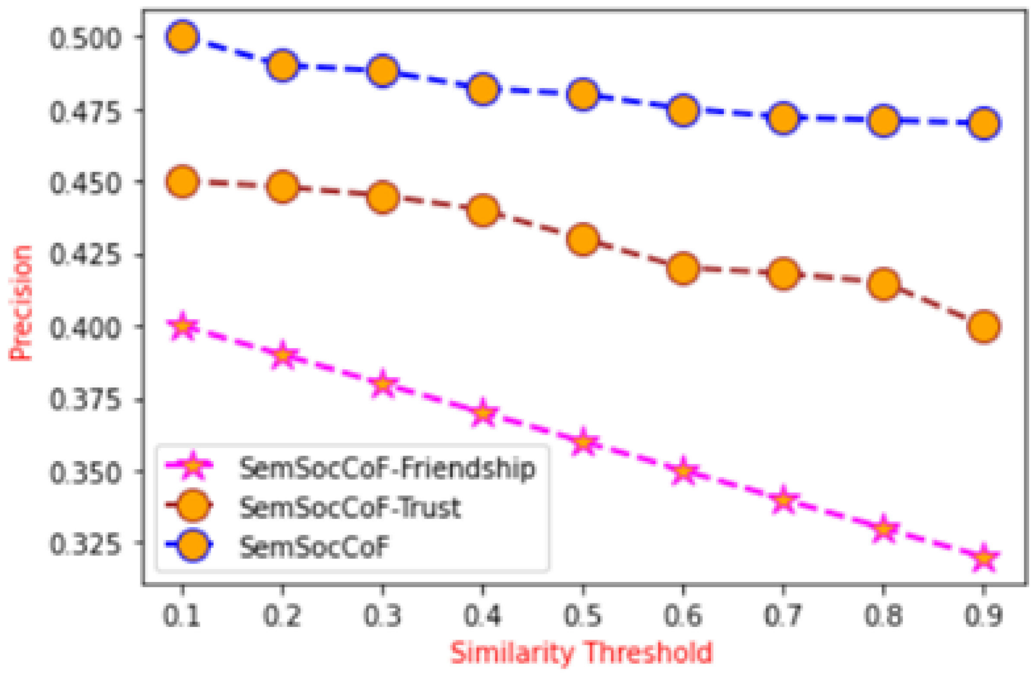


Figure 16. Credibility information contribution in the recommendation system.

The analysis and comparison of the obtained results show that the proposed SemSocCoF model provides remarkable values for precision and F1 measure as 0.5 and 0.65, respectively, even when the similarity threshold is increased from 0.1 to 0.9. The proposed work clearly depicts that two classification strategies can be employed to boost the performance of the RS, the incremental K-means ML algorithm applied to all the users at the initial level and the KNN algorithm applied to the newly added users, which show good results. Our method integrates CoF recommendations with semantic and social information, resulting in an effective collaborative filtering enhancement strategy for friend recommendations in social networks when compared to the other related work [30] with a precision of 0.49 and an F1 measure of 0.64.

Table 4 provides a comparison of the proposed study with existing recent works.

Table 4. Comparison of proposed with existing methods.

Study and Year	Methodology	Remarks
Fathima Mol et al. (2015) [42]	This system extracts the lifestyle of the user. In order to extract lifestyle, authors considered sensor data, messages, applications installed, and MP3 files stored in the smartphone. The system recommends potential friends if they share similar lifestyles.	This study concentrates only on the semantic approach, and the accuracy claimed is also nominal.
Srikantaiah K C et al. (2021) [35]	The authors used the KNN algorithm for recommendations. The authors used each user's personality traits and conduct, which were used to help him/her find new users with the same temperament.	This algorithm does not take into account all neighboring points at the same time in order to bundle a single point. When users are looking for neighbors or other users who have factually demonstrated similar preferences to a certain user, bottlenecks occur.
Lyes Badis et al. (2021) [43]	The authors used a collaborative filtering approach to recommend content in P2P social networks, claimed P2PCF enables privacy preservation, and tackled the cold start problem for both users and content.	The proposed approach assumes that the rating matrix is distributed among peers, in such a way that each peer only sees interactions made by their friends on their timeline.
Proposed Model	Social data are merged with the CoF recommendation. In order to improve performance in the recommendation process, two classification techniques—incremental K-means and K-NN algorithms—are also included.	The suggested study improves the recommendation algorithm by fusing together collaborative, semantic, and social filtering techniques (SocF). The results with the Yelp social network indicate that, in comparison to the user-based CoF algorithm, merging semantic and social data with the CoF algorithm enhances recommendation accuracy.

5. Conclusions

The proposed system showcases improved collaborative filtering (CoF) strategy developed for friend recommendations in social networks. The CoF recommendation is combined with social data in the proposed methodology. Furthermore, two classification techniques, incremental K-means and K-NN algorithms, are incorporated to boost the performance in the recommendation process. The results of the testing process using the Yelp dataset reveal that the suggested methodology is highly effective than the CoF with respect to precision and F1 measure. User semantic and social information is considered in the proposed method. The proposed work results in a better recommendation algorithm based on hybridizations of collaborative, semantic, and social filtering (SocF). The obtained results with Yelp social network suggest that combining semantic and social data with the CoF algorithm improves recommendation accuracy when compared to the user-based CoF algorithm. Furthermore, because the system may offer a list of other relevant users to a given user based on semantic and social information, this combination completely eliminates the cold start problem. Finally, the results proved that the credibility information provides value to the recommendation system. The limitation of this study is that it does not consider all nearby points simultaneously in order to bundle a single point, but instead repeatedly only considers the closest point based on a selection approach utilizing a distance vector. However, other types of information, such as information about close/distant friends, influence, and local/global trust, could be incorporated into the proposed model in order to enhance the quality of the recommendations. On the other hand, as part of our ongoing research, evaluating strategy for a virtual community of learners can be the future extension. In the future, we will try to incorporate dynamic graph neural networks into social recommendation systems to more effectively mine users' possible preferences, which is anticipated to enhance recommendation systems' performance even more.

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