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Social Relations and Methods in Recommender Systems: A Systematic Review

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Abstract

With the constant growth of information, data sparsity problems, and cold start have become a complex problem in obtaining accurate recommendations. Currently, authors consider the user's historical behavior and find contextual information about the user, such as social relationships, time information, and location. In this work, a systematic review of the literature on recommender systems that use the information on social relationships between users was carried out. As the main findings, social relations were classified into three groups: trust, friend activities, and user interactions. Likewise, the collaborative filtering approach was the most used, and with the best results, considering the methods based on memory and model. The most used metrics that we found, and the recommendation methods studied in mobile applications are presented. The information provided by this study can be valuable to increase the precision of the recommendations.

Keywords

Collaborative Filtering, Recommender Systems, Social Relationships, Systematic Review, Trust.

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I. Introduction

Due to the large amount of information traffic generated by social networks, researchers are presenting various techniques in the recovery of relevant information. The delivery of personalized and adaptive content is a research problem in information retrieval (IR) and recommender systems (RS). Collaborative filtering (CF) is the most widely used model with the best results in RSs [1]. In general, RSs are classified into collaborative filtering and content-based filtering (CBF) [1] [2]. CF estimates the interest of an item according to the interests of 'similar' users to the target user, with item ratings being the most used information in CF [3]. Likewise, collaborative filtering algorithms are divided into two main categories: memory-based and model-based methods. Memory-based methods use similarity measures that act on the user-item rating matrix.

The similarity metric is used to calculate the distance between a user-item pair. Model-based methods, on the other hand, use machine learning algorithms [4]. The scarcity of data (less information) causes problems such as cold start. This lack of information on the scalability of the system affects the recommendations [1]. Researchers agree that using a user's contextual information can improve recommender system performance. However, the primary concern in designing a system with context information is finding those factors that are of value for prediction or recommendation. Another essential aspect to consider is privacy and security [5]. The authors acknowledge as a strategy, to use additional information, provided mainly from social networks in the recommender systems to reduce these drawbacks, such as the use of context information (time and location) of the event [6], user-generated tags [3]. The social influence derived from friendship relationships and interactions between users of a social network can be used to improve the accuracy of recommendations [7]. Today, social networks are used by millions of people. Virtual sociability between people can occur through publications, comments, images, likes, etc. Social networks, such as Instagram, allow us to publish photos (and videos) for your followers. In this sense, Twitter will enable us to post text with a character limit, or in Tinder, it is possible to contact people within a certain radius to make appointments, which are some examples. Applications such as Foursquare, Facebook Places, and Yelp are popular social networks among location-based services, allowing users to share their geographic location and location-related content online quickly. Other types of social networks are social event-based, such as Meetup, for group meetings.

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The objective of this work is the analysis of the current recommendation methods, the algorithms they use and whether information about social relationships is taken into account. The present article is organized in the following way: Section II defines the methodology used to search for the primary documents in this paper; Section III reports the results of the study and, finally, conclusions are presented in Section IV.

II. Method

This paper uses the systematic literature review (SLR) methodology proposed by Kitchenham and Charters [8]. This method is rigorous and well-defined, allowing us to obtain a structured and well-organized report with a clear definition of how the process is carried out. The objective is to specify research questions and to search for relevant studies considered as primary articles, identifying the state in the research area, as well as evaluating the contributions and gaps to draw partial conclusions for each research question and to build an overall outcome of the report. The search was divided into three phases: planning the review, conducting the review, and reporting the results. Each phase is explained in the following subsections.

A. Planning the Review

1. Identification of the Need for Revision

The introduction mentioned the drawbacks of a recommender system due to the constant growth of information. For this reason, the researchers present various techniques for recovering relevant information. However, with the use of social networks, it has been possible to obtain meaningful data from the user (preferences, activities, location, friendships, etc.), which has improved the RS's accuracy. However, the need arises to analyze what information in the user's social context is useful and would allow the recommendations to be improved. In this paper, we studied which information describing social relationships is used in RS.

2. Specification of Research Questions

The objective of this paper is to provide answers to four research questions (see Table I).

TABLE I. Research Questions

	Description
RQ1	Which social relations information is considered in the construction of recommender systems?
RQ2	What methods or tools are used by RSs that consider social relations information?
RQ3	How are recommender systems that employ social relations evaluated?
RQ4	Which RS applications use social relations information?

The answers to these questions can be easily linked to the objective: to identify social relationships as information (RQ1), to know methods or techniques that implement RSs with this information (RQ2), to know the impact of their use on the accuracy of recommendations predictions (RQ3) and, besides, to identify the applications that use this kind of information (RQ4).

3. Search Method Definition

Two search methods were chosen and applied sequentially: automatic search and snowballing search. In the first instance, a search for primary articles in digital libraries was performed. Three databases were used. After obtaining a series of primary papers, we performed the snowballing technique proposed by Wohlin [9]. In terms of the data sources of the papers to be included in the search process, we selected the Scopus, IEEE, and ACM Digital Library electronic databases, as they fulfill the following requirements [10]:

- The database is available for us through our institution.
- The database can use logical expressions or a similar mechanism.
- The database allows full-length searches or searches only in specific fields of the works.
- The database allows additional filtering options such as publication year or publication language.
- The databases contain the most relevant journals and conference papers in the field of computer science.

The review period was from January 2014 to March 2021 because this area is considered very recent. An advanced search was conducted using these keywords: ("recommender system" OR "recommendation systems") AND ("social relations" OR "social network" OR "social influence") AND ("context" OR "context-aware").

B. Conducting the Review

This section describes the selection criteria for the primary papers, the process of searching and selecting studies, a synthesis of the data extraction, and an explanation of a validity check of the set of documents obtained.

1. Defining Exclusion and Inclusion Criteria

A set of inclusion and exclusion criteria was defined in this systematic review. Specifically, five inclusion criteria (IC) and the corresponding four exclusion criteria (EC) were defined:

- IC1: Type of publication: Empirical research and peer-reviewed articles and systematic reviews. AND
- IC2: Recommender system: inclusion of social relations information. AND
- IC3: Keywords defined in the search: "recommender system", "recommendation systems", "social relations", "social network", "social influence", "context", "context-aware". AND
- IC4: Period: Published from January 1, 2014 to March 31, 2021. AND
- IC5: Publication criterion: Written in English, any country.

According to the exclusion criteria:

- EC1: Type of publication: No original data, such as reports, opinion studies, essays, or comments and no research. OR
- EC2: No abstract available (first screening). OR
- EC3: Study could not be retrieved (second screening). OR
- EC4: The paper is not written in English.

2. Search Process and Study Selection

We used a combination of keywords in the search. It is important to mention that different combinations of search terms were applied to establish a result that maximizes retrieval (trying to track all the literature) and accuracy (that the articles found are relevant). Two search methods were used, the automatic search and the snowball search. These methods were divided into five steps to be applied in the searching of papers and to select a set of primary documents to extract the data for presentation in this review. The first step for study selection is an automatic search. This process involves applying search strings to digital databases to obtain the first set of primary studies. The second step is the analysis of the title of the selected papers: in this step, the inclusion/exclusion criteria, defined above, are applied. The third step is the analysis of metadata. We took the metadata found in the results of the previous phase studies. These metadata refer to the abstract and keywords of each article and determine whether they meet the selection criteria. The fourth step is the analysis of the full text. In this step, the full text of the articles was obtained to carry out a more exhaustive analysis of their compliance with the selection criteria. Those that met the inclusion criteria were chosen. The fifth step is the snowball search technique. The last step consists of applying the selection criteria to the research works found in the second search method: The snowball search technique. The aim is to select the documents that may have escaped the automatic search to find all possible evidence. This method consists of reading the list of references (Backward Snow Balling) for each article in the set of items and analyzing the quotes made on these articles (Forward Snow Balling), to find other sources or primary articles.

3. Data Extraction and Synthesis

As we mentioned above, the implementation of all steps of the research method described in the previous section resulted in 109 articles considered as primary study publications between January 2014 and March 2021. These detail or propose the development of a recommender system using social relations information. The results of each step of this work are described below.

The results obtained after carrying out this process are described through a PRISMA flow [11] (Fig. 1) :

After applying the search strings in each source, 563 papers were collected, of which 266 are from Scopus, 198 from IEEE Xplorer and 99 from ACM Digital Library.

- After removing 140 duplicated papers. Once the criteria were applied to title, abstract and Metadata, there are 165 papers (39 % of the unique papers retrieved).
- 103 full-text papers were then analyzed. (62 articles were excluded). Six papers were added by applying the snowballing search.
- Finally, a total of 109 papers were analyzed (25.76% of the unique papers retrieved).

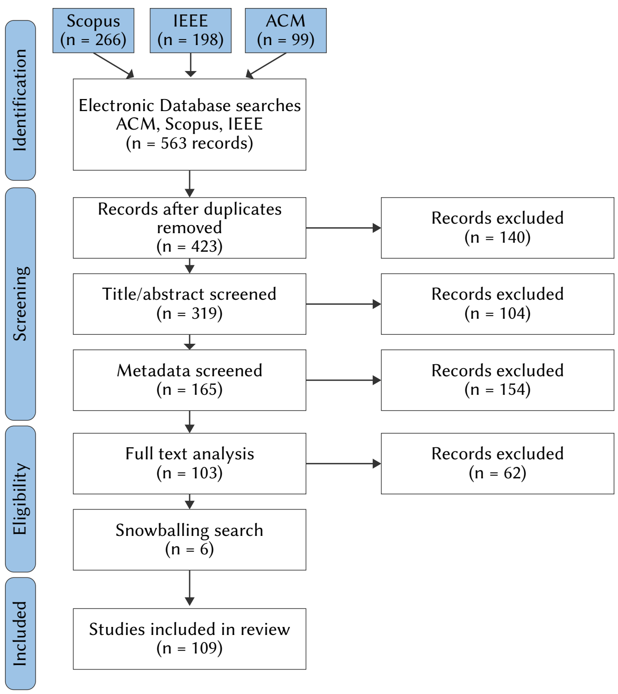

Fig. 1. PRISMA flow. Adapted from [11].

4. Validation Control

To reduce bias and subjectivity in the article selection process, two researchers were randomly selected to analyze a series of articles and, under their criteria, determine which items met and did not meet the selection criteria. The researchers worked from steps two through four of the search and selection process described above. To do this, 150 articles (35% of the total obtained in step 1) were randomly selected for each reviewer. Still, there was an attempt to maintain an overlap of 15 articles and reduce bias among reviewers. The papers accepted by each reviewer were incorporated into the primary set of documents, and no decision problems arose between the repeated documents analyzed by each reviewer.

C. Reporting Results

To develop the analysis of the primary studies, section III of this paper presents a report of the results obtained (last step of the applied article selection methodology).

III. Results

In this section, the results of the systematic review are reported and discussed to answer the four questions mentioned in the previous section. Table II summarize the main results of this review.

Following, we describe the main results organized by different dimensions: a) social relations information considered in recommender systems; b) evaluation of recommender system that implement this type of information; c) methods or tools used by RSS who consider social relations information and d) recommender systems applications that consider social relations information.

A. Social Relations Information Considered in Recommender Systems

As an answer to question RQ1, the works analyzed to show that the information considered as social relations are categorized into three main groups. Being trust, friend activities, and interactions between users. However, these groups are not disjunctive (see Table I).

1. Trust Among Users

Trust is defined as the richness of interactions and commitment among network members that produce positive results. In a general sense, it indicates the existence of affinity between users [35]. Trust is useful in improving the accuracy of recommendations [46]. In turn, [57], [61] states that recommender systems can benefit from incorporating relationships of distrust by considering specific differences between users. The review noted that trust relationships might be explicitly visible or calculated [62]. Both [36]–[39], [46], [61]–[66] assume that the value of trust is explicitly proportionate. That is, in their work, they assume the existence of trusted networks between users. The social network's Epinions and Douban allow the user to explicitly specify other users as trusted (to the trusted list) or untrusted (to the blocked list) if the content is valuable or not useful to the user.

Depending on each approach, the authors choose different ways to calculate the trust value. In [40], they raise the concept of trust transitivity, i.e., if the user trusts user b and user c, then user a trusts user c. In [41], they adopt the confidence calculation from the number of followers. That is, if the user "a" follows user "b" and friends of "b", then user "b" has a high confidence value. Another way is to evaluate the degree of trust between two users based on the preferences of the friends [42], the number of friends in common [43] or through social interactions (comments, publications) [40], as well as to consider the time factor, denoting a higher level of trust in recent interactions [44], [45].

However, some authors choose to classify trust according to different criteria. In [35], they propose a calculation involving two types of confidence. On the one hand, popular trust describes how popular the user is (if people read their posts, many followers, etc.). On the other hand, engagement trust describes users who engage in the social network, such as replying to posts, sending friend requests, etc. Similarly in [47], they consider local trust according to the user profile (qualifications, experience) and global trust according to their public information. Another way to measure trust is according to the reputation of the user, according to the number of users who trust him [48].

2. Friend Activities

According to [12], people are often influenced by their friends and neighbors and tend to visit places that their friends have already visited. Also, people do not usually do activities alone, but do them together [23]. In this study, places visited and/or participation in events held by users was considered social activities. Social networks such as Foursquare or Yelp allow users to rate their experience according to their experience and the places they have visited. Similarly, Meetup enables users to rate events in which they have participated.

Location-Based Social Networks (LBSN) allow users to check-in specific locations (points of interest, POIs) where they are and write a review of the location. Each check-in enables users to obtain

TABLE II. General Summary

Social Relations Information Considered in Recommender Systems		
Friends' activities	[6], [12]–[34]	
Trust among users	[4], [35]–[66]	
Interactions between users	[5], [6], [15], [27], [30]–[32], [34], [44], [67]–[111]	
Evaluation of Recomender System that Implement this Type of Information		
Accuracy	[19], [41], [42], [91], [107]	
Recall	[1]–[3], [15], [20], [22], [23], [28]–[33], [41], [42], [44], [49], [50], [54], [56], [64]–[66], [69], [76], [78], [80], [103], [110], [112], [113]	
Precision	[1]–[3], [14], [15], [19], [20], [22], [23], [28]–[33], [41], [42], [44], [48]–[50], [54], [56], [60], [66], [69], [72], [73], [76], [78], [80], [97], [98], [100], [103], [110], [112], [113]	
F-measures	[3], [16], [20], [22], [29], [41], [42], [44], [49], [56], [69], [110], [113]	
G-measures	[41], [42]	
Hit rate	[72], [74]	
NDCG normalized discounted cumulative gain)	[3], [6], [17], [21], [28], [50], [51], [71], [72], [74]	
MAP (mean average precision)	[28], [50], [80]	
AUC (average area under curve)	[1], [16], [71]	
Coverage	[1], [4], [80]	
Error measures	**Mean absolute error (MAE)**	[1], [4], [27], [43], [51], [53], [58], [59], [63], [68], [76], [77], [90], [102], [106], [112]
	Mean square error (RMSE)	[1], [43], [51], [63], [68], [69], [76], [77], [90], [102], [106]
	Normalized Mean Absolute Error (NMAE)	[58], [59], [82]
Other evaluations	[87][98][73]	
Methods or Tools Used by RSs Who Consider Social Relacions Information		
Memory-based CF	**Similarity among users**	[4], [42], [54], [56], [58]–[60], [72], [76], [80], [82], [86]–[88], [91], [98]–[100], [110]
	Predict rating	[20], [23], [35], [45], [48], [56], [59], [61], [98]
	Sentimental analysis	[97], [105]
Model-based CF	**Factorization matrix**	[2], [3], [6], [17], [19], [21], [27], [31], [36], [43], [49]–[51], [57], [61], [64], [65], [68], [69], [71], [74], [76], [77], [84], [90], [103], [106]
Network-based recommendation models	**Random Walk**	[14], [15], [29], [38], [78], [113]
	PageRank	[62], [64], [111]
	Hyperlink-Induced Topic Search (HITS)	[29], [33], [41]
	Louvain modularity algorithm	[62]
	K-means	[89]
	Latent Bias Model (LBM)	[95], [107], [108]
	Association Rules	[32], [94]
Recommender Systems Applications that Consider Social Relations Information		
Social context	**Brightkite**	[15], [16], [28], [29], [60], [78], [80]
	Book-Crossing	[69]
	Ciao	[65]
	Delicious	[2], [76]
	Douban	[20], [36], [50], [64], [74], [77]
	Epinions	[4], [36], [38], [46], [50], [57], [61], [62], [64]–[66]
	Facebook	[73], [86], [88], [94], [104]
	FilmTrust	[59]
	Flixster	[4], [74]
	Foursquare	[14], [16], [23], [29], [30], [33], [60], [72], [78], [103], [113]
	Gowalla	[15], [16], [23], [28]–[32], [60], [78], [80], [103]
	Renren	[106]
	Meetup	[6], [17], [19]–[22], [104]
	MovieLens	[3], [69], [76], [112]
	Lastfm	[3], [58], [76]
	QWS	[82]
	Yelp	[27], [28], [43], [77]
	Weeplaces	[31]
	Weibo	[68], [71], [90], [106]
Health context	[47], [87]	
Educational context	[42], [84], [100], [111]	
General computing context	[25], [26], [73], [82], [86], [88], [91], [95], [98], [99], [107], [108]	

information such as latitude and longitude of the location, time, and review, among others. The recommender systems used in these social networks recommend points of interest according to the use of information provided by the check-ins; such as considering the check-ins made by the user's friends [12], [23], [28]–[33] or the frequent check-ins [13]–[15], [34]. Another way is according to the popularity of a place, by estimating an average check-in count of friends [31] or by limiting the geographic area concerning the friends' domicile and locations visited [34]. In contrast, in [16], they do not recommend POIs but instead friends, considering information such as frequency and proximity (location) of check-ins.

In turn, in Event-Based Social Network (EBSN), users can create, promote, and share social events. In this sense, referral systems suggest events on different topics to users according to their tastes, proximity, and time [17]. When a user is invited to an event, he or she has a pending request (RSVPed), in [6], [18], [19] the authors use the amount of RSVPed that friends have as information to recommend events. In [20], [21], they assume that the participation of a friend in the event can influence the user, as well as, if a user often participates in events organized by an organizer, the probability that he or she will attend other similar events organized by the organizer will be high. Besides, the average rating and contents of events held are considered [22].

Previously, activities performed by users on social networks were mentioned that the researchers assume "influence" in the recommendations. The following are activities or actions carried out by users, in a general sense, that the authors use as information in their work proposals:

- The use of friends' short- and long-term preferences (or interests), with the short term being the last interest or preference seen in the previous browsing session and long term being an average of the importance [24].
- Evaluating the actions of friends, considering them as actions to copy, create and follow personal processes, is understood as an individual process to a set of tasks with a specific order to achieve an objective [25].
- Evaluating the curiosity among friends, according to the evaluation of the item, for seeing if it has an impact on the recommendation. That is, whether it has a high rating, a film, rated by a friend, can cause curiosity in the target user [26].

3. Interactions Between Users

The concept of social networks is commonly seen as interactions between individuals, and they have become very popular in recent times [111]. In general, social networks allow the modeling of social interactions and relationships. The connecting relationship between users in a social network is often referred to as "virtual friendship" [67]. Each user is a node, and each link is an interaction or relationship [62]. The following is a description of some of the interactions found in this work:

- According the type of social connection, the relationship of friendship or of followers/followers [3], [7], [15], [34], [67]–[83], of students [84], [111] or of employees [85].
- list of friends [86].
- common friends [72], [87]–[91].

According to their actions:

- the number of "likes" recorded by the user an in user publications [88].
- the number of common activities (e.g., liked/followed/tagged the same blog/wiki/community) performed [3], [92].
- the number of reactions or comments to published content among users [93], [94].
- sending and receiving tweets between two users [30] [31].
- the number of tweets sent to friends [95].

According to the analysis of interactions:

- analysis of similarity by means of tags between users [96].
- analysis of feelings of comments between users [32][97].
- analysis of feelings about the content of user interactions, (retweet, mentions, likes, comments, etc.) [97].
- analysis of closeness between two people with information provided by mobile devices, in which they adopt records of calls, messages and, in addition, publications on social networks [98], [99].
- proximity analysis based on the number of interactions (messages) and preferred content between two users with respect to date and time [100].
- the proximity analysis between attendees and presenters with respect to frequency and time of attendance at presentations [101].
- analyze the relationship between the user who wrote a review of an article and the user who comments on it [102].
- calculation of the implicit relationships of two users who registered at the same place within a time interval, using two independent approaches, diversity being the number of times they coincided in different places and frequency being the number of times they coincided in the same place [103].

B. Methods or Tools Used by RSs That Consider Social Relations Information

Concerning models, recommender systems are divided into two main categories: collaborative filtering (CF) and content-based filtering (CBF). The collaborative filtering approach is the most widely used, divided into two methods: memory-based and model-based [1]. Both models reported in the analysis are described below:

1. Memory-based CF

Memory-based algorithms are subdivided in two ways: user-based CF and item-based CF [1]. However, the analysis of this work is focused on the similarity between users. The methods most used are the a) calculate the similarity between users and b) predicting rating.

Regarding the a) calculate the similarity between users, it is obtained by comparing the ratings of two users. The classical measures to calculate the similarity between users are the cosine similarity [86], [87], [91], the correlation coefficient of Pearson [4], [76], [82], [98] and Jaccard [42]. In turn, the authors incorporate additional information such as the friendship relationship between users [80], the degree of connection between users according to common friends [87] and the amount of "likes" between them [88], the number of interactions [99], common interests [100] or check-ins between friends [72], [99]. Another implementation is to generate the similarity function using a genetic algorithm model, in this case, using social variables (age, gender, educational background, and relationship status) of the user and his friends [104]. About the b) predict rating; likewise, social influence among users is calculated by the closeness between two users a and b; and user activity a [20], [23], [98] or by the user's reputation (number of users with confidence in user a) [48]. In this way, the final value of influence is used as a parameter in the rating prediction function. Accordingly, the confidence value is calculated according to the level of trust or distrust [61], by the popularity and commitment of a user concerning the rest [35] or according to the level of trust between user interactions for the time [45]. Also, using sentimental analysis of user tweets, assuming that the emoticons describe negative and positive facial expressions; sentimental similarities are computed by Karhunen-Loeve (KL) transform [97], or the implementation of standard algorithms such as K-nearest neighbor algorithm ID3 to classify feelings into positive or negative [105].

2. Model-based CF

Memory-based recommender systems are easy to implement and understand their algorithms. However, these systems are not practical when dealing with large numbers of users and items. Model-based recommender systems arise later to avoid this drawback [112]. These RSs require a prior learning phase to determine the model's optimal parameters before making a recommendation. Once this phase is complete, RSs can quickly predict user ratings [1]. Within this model-based CF, there are grouping models, network-based models, Bayesian models, and linear factor models, such as the factorization matrix [51]. The MF model allows for the modeling of the intrinsic characteristics of each user and each item. The latent factor model can be divided into two types: basic factorization matrix (MF) that only uses rating matrix to make predictions, and those that add information to MF that are content information, social information, and context information [76]. The following is a list of additional information that researchers incorporate into their proposals: user attributes [43], user and event characteristics [6], [17], [19], [21], check-ins between users [31], social connections (friend, follower/follower) between users [2], [3], [68], [69], [71], [74], [77], [84], [106], trust [36], [49]–[51], [61], [64], [65], [103], implicit trust (according to places visited in common) [103], affinity [76], distrust [51], [57], [61], item categories and keywords [90], tags between users and user interactions [3].

3. Network-based Recommendation Models

Social networks are modeled as a network with user nodes and items connected by edges that describe the relationships. In this sense, they apply models such as random walk for a recommendation of friends [29], points of interest (POI) [14], [15], [78], [113], products and services in electronic commerce [38]. In addition, recommender systems use ranking algorithms to evaluate items such as PageRank [62], [64], [111], Hyperlink-Induced Topic Search (HITS) [29], [33], [41]. Also, community detection algorithms, like the Louvain modularity algorithm [62], K-means [89]. On the other hand, in [95], [107], [108], they propose a Latent Bias Model (LBM). LBM allows the use of appropriate terms to capture the importance of different characteristics for prediction, such as the friendship relationship. The use of deep learning has been successfully applied in the field of RH, achieving a significant improvement over traditional models [12]. Also, in [32], [94], they implement data mining to generate association rules for obtaining suggestions.

C. Evaluation of Recommender Systems That Implement This Type of Information.

The authors use several metrics to validate their research. Generally, they use datasets to evaluate the performance of the recommender system. However, Table II summarizes the metrics used. The most used metrics are described below.

1. Accuracy

Accuracy is a well-known and used metric in the field of Artificial Intelligence; it measures the closeness of a measurement to the real value given by a system [41], [42]. The ACC is the fraction of all correctly classified instances, and it is a metric used to measure the classification quality of a classifier [19]. The accuracy in a recommender system is determined by the number of satisfactory recommendations for the number of possible recommendations [41] (see Eq. 1). For example, in [91], they measure accuracy by first asking users to report the areas they expected to visit in the context of a shopping trip. They recommend the route and record the areas they attended.

$$accuracy = \frac{number\ of\ successful\ recommendations}{number\ of\ possible\ recommendations} \quad (1)$$

2. Recall

The Recall metric is a metric used in the Recovery of Information Retrieval (IR), in the field of user referral systems it is essential to receive recommendations in an orderly manner, from best to worst. The metric recall is the ability to obtain all satisfactory recommendations present in the pool [41]. For example, in [44], to evaluate the buddy recommender system, the recall metric corresponds to the number of trusted friends returned by the method compared to the total number of actual trusted friends for each user.

3. Precision

Like recall, accuracy is a metric used in IR, by which, it describes the fraction or proportion of instances received that are relevant [42]. Of the articles analyzed, the precision metric is the most used. For example, in [97], the accuracy in the Top-k recommendation is defined as the ratio of the number of relevant users to the number of recommended users for a given k (see Eq. 2). In [44], the accuracy is the number of actual trusted friends that were returned by the system compared to the total number of returned friends. However, the precision value depends on the size of the list, k value [72].

$$P@k = \frac{number\ of\ relevant\ users\ of\ top\ k\ users}{k} \quad (2)$$

4. F-measures and G-measures

F-measures defines the harmonic mean of the precision and recall metric [42]. That is, they try to join the precision and recall values in a single value. It is essential to evaluate the conjunction of these two metrics since optimizing one metric by decreasing the other is unaffected. The parameter β allows weighting the precision and recall in different ways. By varying β, it is possible to obtain different values of these metrics [41] (see Eq. 3). F-measures refers to true positives to the arithmetic mean of expected and actual positives. On the other hand, the geometric mean (G-measures) of recall and precision effectively normalizes the true positives to the geometric mean of the predicted and actual positives [3], [41].

$$F_\beta = \frac{precision\,.\ recall}{(1-\beta).precision + \beta\,.recall} \quad (3)$$

5. Hit Rate

Hit rate shows the proportion of users who are given at least one true recommendation. It is a metric that is independent of the size of the output list. It is 1.0 if the output list contains at least one true recommendation, otherwise 0.0 [72].

6. Error Measures

The error rate can be reduced to a single evaluation metric by taking the mean absolute error (MAE) or the root mean squared error (RMSE). Whatever the error metric is used, the main objective is to reduce this error and try to generate customized lists that the user will consume and give an excellent rating of the recommended items [63]. Therefore, a small value of MAE (see Eq. 4) or RMSE (see Eq. 5) means high accuracy in the recommendation [90], [102], [106].

$$MAE = \frac{\sum_{(i,j)\in}|R_{ij} - r_{ij}|}{|T|} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{|T|}\sum_{(i,j)\in T}(R_{ij} - r_{ij})^2} \quad (5)$$

Other metrics used in top-n recommendations are nDCG (normalized discounted cumulative gain) [6], [17], [21], [28], [71], [72], MAP (mean average precision) [28] both metrics consider the ranking (or range) of the recommendations. Another metric used is

AUC (average area under the curve) [16], [71]. The higher the NDCG value, the better the ranking list [71].

7. Other Evaluations

To evaluate the recommendation of friends in [87], the authors studied the system over a period. A total of 1787 recommendations were generated, of which 258 (14.44%) were friend requests, and 63% of 258 were accepted. Another way is to analyze user feedback to evaluate user satisfaction with the recommended ads [98]. In [73], they evaluated the recommender system using a group of users who interacted with a television program recommender system to analyze its performance. They assume that the use of social relationship information provided by Facebook showed that the initial results increased accuracy to 10%.

D. Recommender Systems Applications That Consider Social Relations Information

1. Social Context

Location-based social networks (LBNS) allow users to check-in, rate, and comment on their experiences in a place. In analyzing the articles, the authors evaluate their proposals on datasets such as Gowalla [28], [30]–[32], Brightkite [15], [16], [28], [29], [78], [80], Foursquare [14], [28], [30], [72], Yelp [28], [43], [77], Weeplaces [31]. The recommender systems used by these online networks allow for the recommendation of points of interest (POIs) in a general sense (hotels, restaurants, activities, among others). However, in [32], they recommend places to shop (shops in shopping) or popular activities as a point of interest [29]. Like the LBNS, the authors use online opinion networks to evaluate their systems. Social networks such as Epinions or Douban allow the user to comment on articles (such as films, books, cars, software, etc.). Of the works analyzed, they use Epinions [36], [38], [46], [57], [61], [62], [65] or Doubans [20], [36], [64], [74], [77], these social networks allow users to make ratings, and besides, allows the user to generate their network of trust. In [57], they state that because of the explicit relationships of trust and mistrust, Epinions is appropriate to study trust-based recommender systems.

Event-based social networks (EBNS) are online social networks where users can create, promote, and share social events with other users [21]. Meetup allows us to join a group on a topic and organize events. From the analysis made, the works [6], [17], [19]–[22], [104] Meetup to test their proposals.

In addition to the above, the systems suggest friends to the user according to the following considerations: sentimental analysis of comments [105], tweets between users [97], confidence analysis[41], [44], [52], [66], number of common friends [89], friendly relations [71], the current location of the user [16], [29] or suggestion of accompaniment for activities [23].

On the other hand, the recommendation of contexts according to the degree of trust between users. That is, if the user "a" has confidence with user "b," and the user likes movies, the system recommends movies to user "a" [64]. Another implementation is to propose activities and places according to social groups, previous choices, and location of the user [45].

2. Health Context

The analysis carried out shows a recommender system, in which friends with similar characteristics of cardiovascular problems are analyzed to provide a set of recommendations or suggestions regarding health information [87]. Another application is the recommendation of dental professionals according to a confidence analysis they provide [47].

3. Educational Context

Studies have described a system for recommending teamwork according to student interactions [111], a method for choosing a professional career [42], and another for recommending courses, tasks or exercises to improve student performance [84], or educational resources (e.g., YouTube videos) according to the student's profile [100].

4. General Computing Context

A mashup recommender system is used (integrator and reuse of web services), based on social information that allows web services to be searched [82], [88], arguing that social relations and similar interests among users allow services to be easily recommended. Another application is the recommendation of privacy options in social networks, considering the user's list of friends and friends of friends [86].

Another work focuses on recommendation of mobile applications based on user interactions, considering expert users as contacts in the social network of the user with the highest number of installed applications [99]. Other works recommend TV programs (Electronic Program Guide) [73], movies [26], shopping routes [91], advertising [98], personal processes such as tasks to achieve a goal [25] or multimedia content [95], [107], [108].

In the following section, we present the main conclusions and contributions of this systematic literature review.

IV. Conclusions

The objective of this work was to investigate and analyze what type of information on the existing relationships between users is considered in recommender systems. For this reason, the systematic review is oriented more specifically to this analysis, and a more general systematic review of recommender systems was not carried out. The analysis concluded that the existing methods in recommender systems do not consider the relationships between groups of people if a product/service is recommended. For example, a movie is recommended to you because you will watch it with your father. Also, we consider that the information provided by this study can be valuable to increase the precision in the recommendations, and this can be the principal value of this work for the collaborative filtering area.

- *RQ1: Which social relations information is considered in the construction of recommender systems?* The authors argue that the social relationships between users used as information help to improve recommendations. To obtain a better analysis, it was classified into three main groups. However, these groups are related to each other.
    - Trust: The concept of trust is widely used to describe the degree of a relationship between two people. Trust relationships between users allow for improved efficiency in RSs; however, the trust used as information varies according to the author. The value of trust can be explicit or implicit. It is understood as an exact value when the user chooses his trust (or mistrust) persons. The Epinions social network allows us to generate a list of trusted and untrusted users. Another way to calculate trust is implicit, the degree of trust is calculated by the behavior (check-ins, activities, interactions between users) of the user concerning others in a social network.
    - Friend activities: People are often influenced by their friends and tend to do similar activities such as visiting places their friends have already visited or attended similar events. Besides, people often do not do activities alone, but do them in the company. Thus, the authors use these friend activities as influencing factors in the referral process. This information is usually provided by location and event-based social networks, such as Foursquare, Gowalla, Yelp, and Meetup.

  - User interactions: are widely used by authors as additional information for the recommendation process, or to obtain trust value. Interaction between users is understood as the action or behavior between users in a social network. Being the number of likes, followers/followers, comments, publications, some examples found. However, the relationships of friendship or common friends are the most used. However, the works that consider friendship relationships do not specify the type of relationship or bond (married, engaged, divorced, or other describing a family relationship) due to security issues or lack of information in the datasets used. In [84], [85], [111], they specify a type of relationship between users, such as employee-employer or student-teacher. Therefore, considering the type of relationship between users could further improve the accuracy of recommendation systems.

- *RQ2: What methods or tools are used by RSs that consider social relations information?* RSs based on collaborative filtering use social relationships as additional information. Within CF, we find two models, memory-based and model-based, widely accepted with their advantages and disadvantages. The Nearest Neighbors technique is mainly used to obtain the most similar K users, considering the information detailed in RQ1. This technique employs metrics such as cosine similarity, Pearson correlation, and Jaccard index. Model-based HR techniques start from a previous learning phase to determine the optimal parameters of the model before making a recommendation. Once this phase is completed, RSs can quickly predict user ratings. The most widely used technique is the factorization matrix (FM) because of its high recommendation accuracy and efficiency. FM allows the modeling of the latent characteristics of each user and each item. However, with the constant growth of information, this model presents difficulties in terms of accuracy when suggesting content. Nevertheless, the authors incorporate into the model additional information detailed in RQ1 such as trust (or mistrust) relationships, social influence, user's own characteristics, among others.
- *RQ3: How are recommender systems that employ social relations evaluated?* Various metrics are used to evaluate the efficiency of RSs, such as accuracy, recall, and precision. Accuracy and recall metrics are used to measure the efficiency of recommendations. Accuracy measures the closeness of a measurement to the real value given by a system. Recall takes care of checking what percentage of the items significant to a user were recommended to him. Error measures such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are the most commonly used. It calculates the absolute distance between the suggestions made, and the real rating of the user, considering high performance and a low error value. Other metrics, such as Area Under Curve (AUC), evaluate the quality of the recommendations.
- *RQ4: Which RS applications use social relations information?* The authors use social network datasets to experiment with their proposals. According to the analysis made, datasets such as Epinions and Douban allow the user to generate their own list of trusted and/or distrusted users. Also, location and event-based networks are widely used due to the influence that friends of the user can have in visiting places or attending social events—taking into account information such as current location (latitude, longitude), check-in, or event, as well as the time factor. However, this review determined the clever use of recommendation systems that employ social relationships as additional information.

However, the problems of data sparsity, and the cold start was driven by the constant growth of information has become a complex problem in obtaining accurate recommendations. Today, authors not only consider the historical behavior of the user but also find contextual information of the user, such as trust relationships, friendship relationships, activities of friends, time information, location. Consequently, many studies implement recommendation models that integrate various social factors to improve their efficiency and alleviate problems of data sparsity and cold start. In contrast, the computational cost is increasing and complex.

We found studies that show that their social circle influences people in decision making. Each person influences to a greater or lesser extent according to the underlying context. In this sense, it is interesting to know in what context this happens; that is, a parent's opinion has a more significant (or lesser) influence than that of a friend in a family decision.

This review has shown how papers employ this strategy in the field of recommender systems. This is due to the constant growth of information generated by social applications. For example, if a person has a friendship relationship with another person, they may share the same tastes; in this sense, we obtain relevant, valuable information in recommender systems to improve their suggestions by applying this hypothesis.

This work provides a general classification of the types of social relationship information. Each information was identified, analyzed, and classified to obtain a better interpretation. In turn, in each group, there is a subclassification to improve their interpretation. Similarly, the methods implemented by the recommender systems for this type of information were identified and analyzed. Likewise, this work describes the different metrics used by researchers to evaluate their recommender system proposals. Finally, a classification of the applications that consider social relationship information according to the contexts (social, health, education, general) is presented.

In this sense, this work provides comprehensive information on the use of social relation information in the field of recommender systems. An exhaustive work has been carried out, following a consolidated methodology. So, this work covers fundamental pillars for future work, such as identifying the information, the methods that use it, its evaluation, and the field in which it is applied.

As future works, we will carry out a study applied to specific contexts such as academic, tourism, social. The aim is to identify which information is relevant according to the applied field and to propose new proposals for precision improvements based on the results obtained. Besides, the results of this systematic review have allowed generating suggestions about some of the recommendation methods studied in a mobile application. That is, using information about a specific user (user profile) and, mainly, adding information about their social link (friend, brother, married, brother-in-law, boyfriend, etc.) with other people. It is also intended to extend this prototype to different contexts, bearing in mind that the user's social links are closely linked to the scope of application. Also, we will analyze how our proposals behave using the evaluation metrics identified in this work. The aim is to obtain results that minimize problems such as cold start or lack of data.

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