Identification of Social Influence on Social Networks and Its Use in Recommender Systems: A Systematic Review

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Abstract: Currently the popularization of social networks has encouraged people to have more interactions on the internet through information sharing or posting activities. Different social media are a source of information that can provide valuable insight into user feedbacks, interaction history and social relationships. With this information it is possible to discover relationships of trust between people that can influence their potential behavior when purchasing a product or service. Social networks have shown to play an important role in e-commerce for the diffusion or acquisition of products. Knowing how to mine information from social networks to discover patterns of social influence can be very useful for e-commerce platforms, or for streaming of music, tv or movies. Discovering influence patterns can make item recommendations more accurate, especially when there is no knowledge about a user's tastes. This paper presents a systematic literature review that shows the main works that use social networking data to identify the most influential set of users within a social network and how this information is used in recommender systems. The results of this work show the main techniques used to calculate social influence, as well as identify which data are the most used to determine influence and which evaluation metrics are used to validate each of the proposals. From 80 papers analyzed, 14 were classified as completely relevant regarding the research questions defined in the SLR.

1 INTRODUCTION

The mass adoption of network communication technologies has significantly expanded the population that are aware of social networking concepts and interested in the data produced there. A number of people currently actively manage an explicit network of virtual friends, contacts, associates and internet addresses that make up their family, social, and professional lives. An easy and common way to see how highly connected people exchange information by email messages sent from person to person. The notion of "friends of friends" is easily illustrated in the features of social media applications such as Facebook, Instagram, Twitter, LinkedIn, which offer services explicitly called "social networking". The successions of information shared within these networks illustrate the modern way in which interaction between people has shifted to computer-mediated channels of communication. Social networks are services that allow people to browse and to connect with friends of their friends (Hansen et al., 2011).

Social media encourages users to have more interactions on the Internet by sharing information or posting activities. On social networks, the relationship can be defined by the number of social information shared (eg post, comments, likes) between users (Hendry et al., 2017). Social networks make more visible the ties and connections that have always connected people, such as relationships between teams, partnerships, tribes groups, alliances, companies, institutions, organizations, among others; types of relationships that before the existence of social networks were less apparent (Hansen et al., 2011).

With the information available in social networks, it is possible to detect knowledge that may be useful to offer better products and services to users in different fields. For example, in the field of Recommender Systems (RS), it can provide more accurate item recommendations, in part thanks to social networks, because the mass information produced by online users in social networks creates new opportunities to help researchers and developers better understand the user preferences (Li and Xiong, 2017). The Netflix en-

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terprise uses data from social network, such as Facebook, to discover the friend circle using preferences (ex. titles watched), or crossing people data from different countries with similar profiles to recommend foreign titles.

The large volume of data generated daily makes it harder for users to find what interests them, because of the multiple items/product options available on the internet. Due to this, RS plays a very important role in suggesting items that allow users to have a positive experience when making a purchase or purchasing a product (Lalwani et al., 2015; Deng et al., 2014).

RSs are software tools and techniques that aim to provide users with suggestions for items that are effectively useful to their needs. RS is referred to as "item" which is recommended to an user. An RS usually focuses on generating recommendations for an item type (eg, music, movies, electronics, news), but it can also be for a set of types, or miscellaneous products, such as e-commerce (Prando et al., 2017). Recommendations are all customized to provide useful and efficient product or product suggestions to the user (Ricci et al., 2011).

RS methods that use social information assume that social network data can discover ties of friendship, trust, or influence among users. From these ties of trust, or influence, users are more likely to develop a greater affinity for items purchased by their social ties. Different approaches have been proposed (Yang et al., 2018; Wu et al., 2018; Li and Xiong, 2017; Zhang et al., 2017; Zhou, J et al., 2017) to obtain the degree of social influence that some people cause on others based on information from social networks.

This paper presents a Systematic Literature Review (SLR) approaching different proposals from recent research found in the literature analyzing social network information to calculate social influence and how this information can be useful in RS (Wang et al., 2016).

This work is divided as follows; Section 2 presents the main aspects of previous works in the literature review regarding correlated themes. Section 3 details the process followed to carry out the SLR here presented. Section 4 shows the SLR results. Section 5 introduces the main aspects of the papers classified as relevant to the SLR and the conclusion of the work is shown in section 6.

2 RELATED WORKS AND BACKGROUND

Different approaches have been used by e-commerce, entertainment, services or content platforms to recommend products to their users (Thilagam, 2016). Among the main approaches used in RS, the literature highlighted Content-Based Filtering (CB), Collaborative Filtering (CF) and Hybrid Filtering.

Content Based Recommender System (CB-RS) generates recommendations based solely on the user's profile, that is, on the set of favorite items, or that were searched in the past by the user (Huang et al., 2016). Therefore, the system learns to recommend items that are similar to those one liked in the past.

Collaborative Filtering Recommender System (CF-RS) is characterized by recommending to a user items that other users with similar preferences have enjoyed in the past. Similarity between users is calculated based on the behavior of the ratings they made on the items. These behaviors allow predicting future assessment behaviors for other items. CF-RS is considered the most popular and widely implemented technique in RS (Ricci et al., 2011; Desrosiers and Karypis, 2011).

Hybrid systems are based on combining the techniques, thus using the advantages of one that can overcome the deficiencies of the other and improve the results of the recommendation (Ricci et al., 2011).

An emerging topic in the literature is the social recommender systems, which is based on the assumption that popular items adopted by the user's trusted friends can be recommended to him/her (Li and Xiong, 2017). Some researches in the literature (Xiushan and Dongfeng, 2017; Lian et al., 2016; Wang et al., 2016) have shown that using social network information can be a good resource for discovering relationships of trust, or influence, which can help mitigate popular problems that happen regardless of the approach taken in RS, such as *Cold-start* and *Data Sparsity*, and improve item recommendations in RS.

Wu et al. (2013) carried out a review related with social media applications, associated to where information is created and how it is exchanged in applications such as e-commerce, content-sharing sites, social network sites, virtual community, and collaborative projects. In relation to social influence, the authors presented some examples of studies that aim to identify influential users using some information from social networks and techniques such as PageRank. They also commented about some heuristics employed to calculate the social influence and even about graph models. However, its approach is a little generic, it was not shown, for example, the type of graph technique that were used to model social influence, nor showed techniques that can be applied in RS, nor addressed the type of information employed by previous researchers to calculate the social influence. In social networks there are different data and each of them present particular features that can be more useful to calculate social influence. Then, to know about the data type employed in a particular research should be important to propose new ways of calculating social influence.

Li et al. (2018) showed proposals of techniques to calculate social influence. Despite of the authors have related several techniques, they did not concentrated in proposals that consider influence inside of a group of friends, besides they did not consider applications as RS. Considering that closest friend usually have more affinity, the influence among them is stronger (Gonzalez-Camacho, L.A. and Alves-Souza, S. N., 2018) and more effective mainly for RS. The SLR presented here, focuses on researching of techniques to calculate influence in a group of friends in social networks, identifying the most influential individual into the group. It is also showed the kind of data would be interesting in the calculation of social influence to improve the recommendations.

3 PROCEDURE FOR SYSTEMATIC LITERATURE REVIEW

For a more objective literature review, SLR was proposed following the guidelines of Kitchenham and Charters (2007), who say that an SLR is a method that is previously defined and followed to identify, select, evaluate and synthesize works related to the research theme. This SLR has been divided into three steps: Planning, Execution, and Summary. Each of these steps contains a set of steps that were followed.

3.1 Research Questions and Search Strings

The main research question we tried to answer was:

- There are techniques to identify in social networks the most influential user and/or set of users; was this information used to improve the recommendation?

As search string was defined:

- (”recommender system”) AND (”social network”) AND (”user social relation” OR ”group users” OR ”user influence”)

The databases chosen to search the papers were:

- Scopus, IEEE, ACM e Web of Science.

The choice of these bases was based on the trust of their content by the computing area and the access to the full text of the papers, which is guaranteed by the University.

3.2 Inclusion and Exclusion Criteria

Table 1 shows the inclusion and exclusion criteria defined for the initial selection of papers.

Table 1: Inclusion and exclusion criteria.

Inclusion	Exclusion
The research uses social networking information to determine the most influential friend	The research is not written in English
The research is related to recommender systems	
The research identifies the type of user social relationship within the social networks	
The research was published in a journal or conference between 2017 and 2019	

3.3 SLR Process

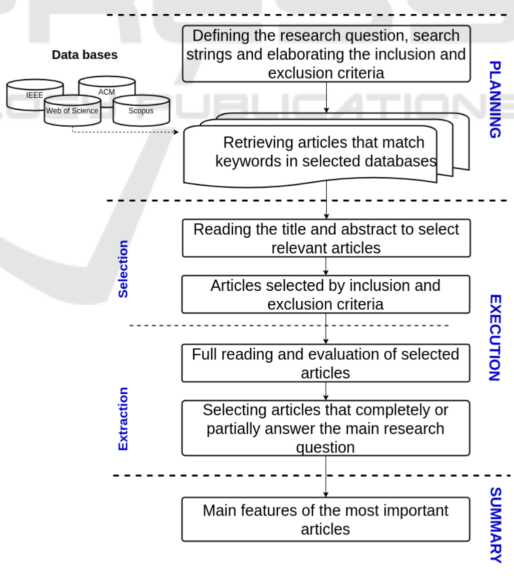

Figure 1: SLR process diagram.

Figure 1 presents a diagram summarizing the process followed in the method employed to perform the SLR. Each part of these process is detailed below:

- Planning: At this stage, a protocol was elaborated, with the research question and related keywords. The search strings were elaborated and the search databases were chosen. Additionally, the inclusion and exclusion criteria were determined for the research selection. Finally, five evaluation questions were defined to assist in the final extraction of the most relevant research and they are specified in Section 4.

- Execution: This phase is related to retrieving papers that satisfy the search conditions. For this, the search strings were applied to the selected search bases, along with the criteria defined in the planning stage. For selecting the most relevant works in relation to the research question, the research was divided into two further steps:
  - Selection: only the title and abstract of the papers were read. Following the inclusion and exclusion criteria, the papers were selected for full reading or discarding. Filtering to determine the relevance of the paper was also used.
  - Extraction: The papers selected in the selection stage were completely read and evaluated to estimate their importance within the scope of the research.
- Summary: At this stage, we obtained the final results of the SLR. As a result, the main characteristics of these works are summarized.

4 SLR RESULTS

Figure 2 shows the results from applying the search strings to the databases already mentioned. This Figure shows the number of papers retrieved by publication type. In total, 80 papers were found, of which 47 were published in conferences, 32 in journals and 1 in a book. We preferred not to summarize by search base, because it was not the objective of this work to evaluate or to compare these databases.

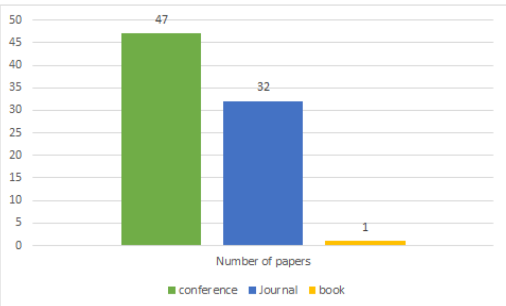

Figure 2: Number of papers by type of publication.

Table 2 shows the number of filtered papers for each step of the execution phase, ending with the total number of papers classified as the most relevant.

Table 2: Number of papers found and selected in the execution phase.

Resume	Number of papers
Total found	80
Duplicates	2
Pre-selected	32
Selected for full reading	24
Final extraction	14

In the extraction phase to evaluate and classify papers in terms of their importance to SLR, five questions were elaborated based on the main research question as follows:

- Q1- Does the research identify communities to define influence?
- Q2- In the research is the community/group identified by any similarity calculations among users?
- Q3- Does the research identify the most influential individual within the group / social network?
- Q4- Is this influence used to improve the recommendation of any item?
- Q5- Is this influence directly related to the degree of friendship?

The score for each question was determined as a binary value (0-1), 1 was assigned if the paper meets the Qi assessment question, or 0 if the paper does not (Gonzalez-Camacho, L.A. and Alves-Souza, S. N., 2018). This score allowed classifying the papers selected for reading in order of relevance and finally, selecting those that could effectively answer the main research question. Each paper was evaluated against each of the 5 questions (Q1, Q2, ..., Q5) listed above. The sum of the scores (S) determined the final grade and the classification of the paper, i.e., ($S = 5$): completely relevant, ($3 <= S <= 4$): partially relevant and ($S <= 2$): not relevant. Table 3 shows the ones classified as completely or partially relevant.

Table 3 also shows which of the questions the paper answered assertively. Papers are ordered by the score (highest to lowest), and the year of publication. As a result, 14 papers were considered to be able to answer the main research question.

5 KEY ASPECTS OF MAIN PAPERS

Tables 4 and 5 summarize the techniques and information set used in the 14 papers selected at the end of this SLR.

Table 4 shows, for each paper, which techniques were used to determine the social influence on the social network. From the set of selected papers it was

Table 3: Classification of papers by evaluation question.

References	Q1	Q2	Q3	Q4	Q5	S
Diaz-Agudo et al. (2018)	✓	✓	✓	✓	✓	5
Yang et al. (2018)	✓	✓	✓	✓	✓	5
Liu et al. (2018)	✓		✓	✓	✓	4
Hendry et al. (2017)	✓	✓	✓		✓	4
Li and Xiong (2017)		✓	✓	✓	✓	4
Bhowmick et al. (2018)	✓		✓		✓	3
Ma et al. (2018)	✓		✓		✓	3
Wu et al. (2018)	✓		✓		✓	3
Jianqiang et al. (2017)	✓		✓		✓	3
Xing et al. (2017)	✓		✓	✓		3
Sumith et al. (2017)	✓		✓		✓	3
Zhang et al. (2017)	✓		✓		✓	3
Zhou, J et al. (2017)		✓	✓		✓	3
Zhou et al. (2017)		✓	✓	✓		3

noticed that, in general, the techniques could be classified into two approaches: Graphs and Heuristics / Graphs. Graphs include the use of centrality measures to determine social influence, while heuristics/graphs involve the use of centrality measures associated with heuristics proposed by the authors, or other different techniques from those commonly used. The graph approach was divided into centrality measures: Eigenvector (Eigen), Degree (Deg), Closeness (Close), Betweenness (Betw). While the Heuristics / Graphs approach was divided into Graph-Based (Gp-B), Page Rank Based (Pr-B) and Other.

From the selected papers, 3 performed graph modeling to analyze the behavior of social network information and applied different graph-centric metrics to determine social influence. The other 10 papers proposed heuristic algorithms for calculating influence. Some of these were based on graph techniques to model social interaction, but included other ways to assess influence, corresponding to Table 4, the technique classified as "graph-based" (Gp-B). Papers which applied different techniques from those commonly used and proposed new ways to identify influence were classified as "others".

When a social network is modeled by graphs, each person is modeled as a vertex and their connections to other vertices are referred to as edges. For analyzing a network, it is necessary to define some metrics that allow, for example, comparison with other networks, tracking changes over time, or determining the relative position of individuals and groups within it (Hansen et al., 2011). Centrality metrics are ways to analyze of social networks by graphs, which allow capturing the importance of a vertex (node) within the network, based on some criteria. These metrics allow identifying people who are most important (have the most connections) by the position in which they are allocated. For example, some people are allocated at the edge, or periphery of the network, while others are allocated more to the center and connected to all other people (Hansen et al., 2011).

The following centrality metrics provide quantifiable measures (Hansen et al., 2011):

- Degree centrality (Deg): is characterized by the number of connections linked to a vertex. When the network is directed, this measure is divided into two: In-degree, which is the number of connections that point into a vertex. Out-degree is the number of connections that originate from one vertex and point to other vertices. Degree centrality is generally similar to a measure of popularity, but inefficient as it cannot differentiate between quantity and quality. For example, by this measure, it is not possible to differentiate between a relationship with the president of the republic and a relationship with the state university.
- Betweenness centrality (Betw): This is a measure of how often a given vertex is on the shortest path between two other vertices. It is a measure that allows evaluating how much removing a person would break connections between others in the network. This gives the highest score to those that serve as a "bridge" to connect to other people in the network. For example, measuring the shortest distance between people who are not neighbors, but are neighbors to other neighbors, and so on.
- Closeness centrality (Close): . With this measure, it is assumed that vertices can only transmit messages or influence their existing connections. A low value means the extent a person is directly connected, or "jump away" from most of the others in the network. For example, vertices in very peripheral locations may have high closeness centrality scores, which point to the number of hops, or connections, they need to make to connect to others far away in the network.
- Eigenvector centrality (Eigen): Allows connections to have a variable value; thus, connecting to some vertices has more benefits than connecting to others. The Eigenvector view is more sophisticated than the other measures of centrality, a person with few connections could score very high if those connections were very well connected, e.g., those that have a high number of messages ex-

Table 4: Techniques used to calculate social influence.

Reference	Graphs				Heuristics / Graphs		
	Eigen	Deg	Close	Betw	Gp-B	Pr-B	Other
Bhowmick et al. (2018)							✓
Diaz-Agudo et al. (2018)					✓		
Liu et al. (2018)	✓						
Ma et al. (2018)	✓	✓	✓	✓			
Wu et al. (2018)						✓	
Yang et al. (2018)					✓		
Hendry et al. (2017)					✓		
Jianqiang et al. (2017)							✓
Li and Xiong (2017)							✓
Xing et al. (2017)							✓
Sumith et al. (2017)					✓		
Zhang et al. (2017)						✓	
Zhou, J et al. (2017)							✓
Zhou et al. (2017)		✓	✓	✓			
Total de artigos	2	2	2	2	4	2	5

Table 5: Social data types used to calculate social influence.

Reference	Social data							
	Fw	Fwe	Ps	R-Ps	Lk	Cm	Mt	Other
Bhowmick et al. (2018)				✓				✓
Diaz-Agudo et al. (2018)	✓				✓	✓		✓
Liu et al. (2018)	✓	✓						
Ma et al. (2018)				✓		✓	✓	
Wu et al. (2018)		✓		✓				
Yang et al. (2018)	✓	✓						✓
Hendry et al. (2017)			✓		✓	✓		✓
Jianqiang et al. (2017)				✓		✓		✓
Li and Xiong (2017)	✓			✓		✓	✓	
Xing et al. (2017)		✓	✓	✓	✓	✓		✓
Sumith et al. (2017)			✓	✓	✓			
Zhang et al. (2017)			✓	✓	✓	✓		
Zhou, J et al. (2017)	✓	✓	✓	✓	✓	✓	✓	✓
Zhou et al. (2017)	✓	✓				✓		
Total Papers	6	6	5	9	6	9	3	7

changed.

- Page rank (Pr-B): such as Eigenvector, page rank measures connections based on their qualification. It is an algorithm used by the Google search engine for information retrieval.

Table 5 highlights the seven data types, whose definition is given below, used by each paper to determined social influence. The data type ”other” refers to ones that appeared less frequently, such as: time when information is propagated in a social network, statistics on the relevance of published content, or type of social interaction not specified. The Results in Table 5 indicate which data appear to have the most weight when assessing social influence on social networks. As can be verified, Re-posting, Commenting, and Followee were the most used to estimate social influence.

- Follower (Fw): set of users who follow a particular user. For example, if user A follows user B ($A \rightarrow B$), A is part of B's followers (Xing et al., 2017). It can also be interpreted as a friendship tie.
- Followee (Fwe): set of users that a particular user follows. For the previous case, user B is part of the individuals followed by A (Xing et al., 2017). It can also be interpreted as a friendship tie.
- Posting (Ps): set of information shared by a user in the social network.
- Re-posting (R-Ps): can be interpreted as information posted by one user, which has already been posted by another.
- Likes (Lk): posted information that is highlighted

by social network users, indicating that they liked the published content.

- Comments (Cm): are the opinions made by users of the social network to the published content.
- Mentions (Mt): This is when in a comment, a user names another user, or particular users.

To evaluate the performance of proposed algorithms to determine social influence of the individuals in a social network most papers used an empirical assessment method (Liu et al., 2018; Ma et al., 2018; Wu et al., 2018; Yang et al., 2018; Hendry et al., 2017; Sumith et al., 2017; Zhang et al., 2017; Zhou et al., 2017). However, there is no widely accepted measure in the literature, at least as far as this research has reached, that serves to verify the performance of such algorithms.

Yang et al. (2018); Li and Xiong (2017); Zhou et al. (2017) used the social influence calculation to make some recommendations. Jianqiang et al. (2017) could adapt the measures *Precision*, *Recall* and F1 based on the identification of a set of reference influential individuals to prove the efficiency of its algorithm. Zhou, J et al. (2017); Bhowmick et al. (2018); Jianqiang et al. (2017) have even not implemented the social influence to recommend items, they instead estimated the efficiency of social influence in the proposed approach.

6 CONCLUSION

This work investigated how the information produced from the different interactions between users in social networks can be very useful in RS. Specifically, papers published in journals and conferences between 2017 and 2019 were collected; their main objective was to identify the most influential individual or group of individuals from mining information from social networks.

Different approaches have been proposed to calculate social influence and the graph was the technique mostly employed to model social interaction. Some of these works used centrality measures to estimate social influence, although many others proposed new ways for this calculation.

The advantage of the graph technique to model relationship among users in a social network is that it allows to not only quantifying these links but also to qualify them, mainly when heuristics and other techniques are added. The social influence model can be different depending on what it is employed for. For example, in a recommender system, the social data types used in the social influence model can receive different weights depending on what is being recommended.

SLR highlighted the most used social data types to estimate social influence. The papers selected showed that the most commonly used data were: number of posts re-posted, number of comments and number of follow-ups that users had in their social network. These three types of data could have a greater weight when proposing a model for calculating social influence.

Finally, the social influence model proposed was concluded to preferably evaluated empirically.

The result of this SLR can be used as a basis for determining the most relevant information that can be extracted from social networks to model different forms of social influence that can be used in recommender systems to improve the accuracy of recommendations.

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