



The Online Social Networks Analysis: State of the Art

Asmae El Kassiri and Fatima-Zahra Belouadha

Engineers Mohoammadia School, Mohammed V University, Agdal, Rabat, Morocco

Key words: OSN, SNA, social mining, community detection, link prediction, similarity analysis, recommendation, influence, trust, e-reputation, opinion mining, experts detection, privacy and security on OSN

Corresponding Author:

Asmae El Kassiri

Engineers Mohoammadia School, Mohammed V University, Agdal, Rabat, Morocco

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Abstract: Nowadays, the Online Social Networks OSN emergence has expanded the scope of these needs. In fact, besides the direct links between users, the OSN have various important information about user profiles, tastes and interactions or activities. This information richness has been exploited in the literature in particular social mining techniques to answer new analytical purposes such as influence analysis, trust analysis, opinion mining, recommendation, e-reputation, protection of privacy and detection of experts.

INTRODUCTION

The OSN (Online Social Networks) are the actual communication tool, providing to their members the possibility to express their tastes, interests and activities and to establish relationships. They store huge amount of information that can be analysed in multiple contexts for varied ends.

The OSN analysis combine the structural Social Network Analysis (SNA) to the social mining technics for nine analysis objectives: similarity computing, influence propagation, opinion mining, expert detection, trust analysis, recommendation, privacy, community detection and link prediction.

The aim of this study is double: presenting the different OSN analysis and capturing the indicators used by according algorithms synthesizing. Therefore, for each analysis cited above, the authors have studied multiple works dedicated to identify the objectives, approaches and metrics proposed to compute the need.

This study is organized in eleven sections. The nine next sections corresponds to the analysis applied to OSN and its objectives. The perspective of this work and a conclusion are the subject of the 11th section.

The similarity analysis: Formerly, the similarity concept was associated to a structural similarity based on network topology and neighboring notion. Then, the similarity has evolved to a semantic similarity exploiting the shared contents on social media to evaluate the similitude between profiles or interests. The two notions similarity can be combined to speak about a structural-semantic-similarity. The proposed approaches are based on three principles.

The neighboring notion (Newman, 2001; Ravasz *et al.*, 2002; Zhou *et al.*, 2009; Leicht *et al.*, 2005; Adamic and Adar, 2003). The hypothesis is that two directly connected persons are similar. It's based on analyzing only the links on the network and it's entitled structural similarity.

The profiles and interests (O'Donovan and Smyth, 2005; Golbeck, 2009; Bhattacharyya *et al.*, 2011; Akcora *et al.*, 2013; Crandall *et al.*, 2008; Huang and Yang, 2012; Davoodi *et al.*, 2012; Anderson *et al.*, 2012): two users with similar profiles and similar interests are similar. To compute it, geodesics and correlations measures, like Person correlation (Resnick *et al.*, 1994; Konstan *et al.*, 1997) and Spearman correlation (Herlocker *et al.*, 1999) have proven their efficiency. This similarity is entitled semantic similarity.

The hybrid approach (Zhou *et al.*, 2009, 2010; Cruz *et al.*, 2012; Xia and Bu, 2012; Aiello *et al.*, 2012) introduce the semantic similarity to compute structural similarity. It's entitled the structural-semantic similarity.

MATERIALS AND METHODS

The influence analysis: The influence analysis objectives are identifying trends and popular topics and maximizing/minimizing the influence in an OSN. The influence maximization is possible thanks to the influent nodes able to diffuse to other nodes. The minimization is made by cutting links between the influent nodes and the other nodes (Liu *et al.*, 2010; Guille *et al.*, 2013; Jiang *et al.*, 2014).

Users activities Saito *et al.*, 2008; Anagnostopoulos *et al.*, 2008; Yang and Counts, 2010; Yang and Leskovec 2010; Bakshy *et al.*, 2012; Guille *et al.*, 2013): Using the number of friends who became active (infected or influenced) after an action (Share, comment, like, dislike, etc.). An active friend is a friend who reacts to an action. The reaction can be a share, comment, like, dislike, etc.

Person popularity (Cha *et al.*, 2010; Lagnier *et al.*, 2012): Using the subscribers of his profile page, his publications and his identifications by other users.

Similarity (Crandall *et al.*, 2008): The similarity is a factor of influence.

Structural measures: Kimura and Saito (2006), Chen *et al.* (2009), Newman (2010), Kim and Yoneki (2012), Mochalova and Nanopoulos (2013), Easley and Kleinberg (2010) and Hinz *et al.* (2011) using the structural information like centrality and the hubs and switches notions.

Topic popularity: Cha *et al.* (2009), Asur *et al.* (2011), Shamma *et al.* (2011), Alsumait *et al.* (2008), Cataldi *et al.* (2010), Guille *et al.* (2013) and Schubert *et al.* (2014) using the frequencies of interactions (visits, shares, comments, subscriptions, evaluations, etc.).

Sentiment analysis: Since 2000, the opinion mining (sentiment analysis) became an active research domain. It's founded on statistic and linguistic technics to estimate persons opinions, sentiments, evaluations, attitudes and emotions for entities and its characteristics and attributes (e.g., organizations, products, services, topics, etc.). The opinion mining is studied in multiple researches for different applications like marketing, recommendation, social and political analysis (Liu, 2012, 2015).

The approaches are based on two steps: First, extracting subjective data to identify sentiments and opinions, second, classifying it into positive and negative sentiments (Liu, 2012; Hu and Liu, 2004). The indicators used for the sentiment analysis from OSN are the evaluations (like and dislike).

Expert detection: An expert is a person having a high-level knowledge and skills to perform a domain task. Detecting experts in an OSN aims giving an experts list having high-levels skills able to respond to an organization or a community request. It's mainly explored for the scientific researches to ensure scientific cooperation and recruitments or human resources management to cover human resources needs (Zhang *et al.*, 2007; Karimzadehgan *et al.*, 2009; Lappas *et al.*, 2009; Lappas *et al.*, 2011; Davoodi *et al.*, 2012, 2013). It can be applied to different networks types like the scientific social networks centred researchers (e.g., ResearchGate) or centred articles like digital libraries (e.g., IEEE Xplore, ACM, CiteSeerx, etc.), the professional social networks (e.g., LinkedIn, Viadeo, etc.), the private enterprise social networks and Questions/Responses sites (e.g., Yahoo!Answers, Quora, Stackoverflow, Comment ca marche, etc.). The objective is identifying experts by estimating their levels skills in a domain and detecting relationships between experts if an experts team is needed to cooperate in the same project. As result, the indicators required for the experts detection are the user's skills and their professional relationships.

Trust analysis: The trust is a bilateral relationship (interpreting a confident feeling). It's asymmetric (not reciprocal), non-transitive and spreadable (nearest people's trend to develop crossed trust networks). A panoply of scientific researchers have analyzed the trust in the OSN in many domains like the security and privacy, the marketing, the recommendation and the clustering (Abdul-Rahman and Hailes, 2000; Dimitrakos, 2003).

The trust analysis exploits the explicit trust declared in OSN. A category of approaches considers the similarity

(Ziegler and Lausen, 2004; Ziegler and Golbeck, 2007), the strength of links based on the frequent interactions, the absence of conflicts between two users (Gilbert and Karahalios, 2009; Xiang *et al.*, 2010) and the influence (Guha *et al.*, 2004; Ziegler and Lausen, 2005; Golbeck and Hendler, 2006; Adali *et al.*, 2010) as indicators of an implicit trust. Another category exploits the graph theory technics and the trust propagation property to elaborate propagation rules and to infer trust links between not connected neighbors in a trust network (inferred trust) (Guha *et al.*, 2004; Hasan *et al.*, 2009; Chakrabortya and Karform, 2012). Another category reuses the popularity and fidelity notions to compute reputation and trust scores of neighbors to predict malicious nodes (predict good and bad reputation), a malicious node is supposed having good trust scores from malicious users. In other approaches, the bad reputation is deduced from the interactions historic (e.g., a passive account becoming suddenly active is likely pirated by a malicious user) (Massa *et al.*, 2005; Caverlee *et al.*, 2008; Nepal *et al.*, 2011).

RESULTS AND DISCUSSION

Privacy and security analysis: On OSN, users trend sharing private information online causing protection problems. This information is mainly targeted to a specific audience category of each user. Otherwise, the social media managers impose to their users a usage policy to have their data exploitation rights. Furthermore, the OSN must protect their users accounts against any attack form and ensure their sensitive data protection (Singh *et al.*, 2014).

This field objective is eliminating the personal data divulgation risks, authenticating shared contents on social media and detecting the web spams and attacks. In other words, the aims are to control contents visibility on OSN to protect privacy against any espionage risk and to identify non-authentic contents and malicious users to protect the author users. The approaches of privacy and security on OSN propose different demarches according the targeted objective. To ensure the contents visibility control, there are three demarches kinds:

Using visibility levels: Exploiting confidentiality parameters defined by users on their profiles elements and shared contents to prevent divulging personal information to non-concerning users (Barbian, 2011).

Using a trust measure: Applying trust learning algorithms estimate trust and prevent divulging personal information to distrusted users (Sherchan *et al.*, 2010; Golbeck *et al.*, 2003).

Using the online reputation: Exploiting explicit or implicit information about online reputation to identify malicious users and neutralize them by social media or reveal them to users to protect themselves (Caverlee *et al.*, 2008; Levien, 2004). To detect attacks and web spams, three steps were identified:

Detecting undesirable elements (spams): An undesirable element can be a shared content (e.g., post, image, video, etc.). To detect spams, algorithms exploit the hypothesis that a spam is an ignored element (e.g., no positive evaluations, no comments, no visits, no private messages with his owner, etc.), able to propagate very rapidly in a brief period. Then, identifying spams is based on user's interactions analysis concerning a shared content and on its sharing intensity on the OSN (Kincaid, 2016; Cao and Caverlee, 2015; Zhenga *et al.*, 2015).

Identifying spammers: It is based on the infidelity notion. The infidelity consists on the fact that a spammer or a malicious user has many contacts, many temporary accounts and a lot of shared contents but little subscribers. Because, a spammer aim propagating his contents to the maximum users and per statistics, a spammer share per day approximatively three times more than normal user but his actualities fil has little interests (Gyongyi *et al.*, 2004; Cao and Caverlee, 2015).

Detecting pirated accounts: It is based on the hypothesis that a pirated account is an account becoming suddenly more active (e.g., more shares, more contacts, more social page's subscriptions, etc.) and less trusted by the OSN users (e.g., unsubscribing from his contents and containers, deleting from contacts list, reporting, etc.) (Gao *et al.*, 2012; Zhenga *et al.*, 2015).

Community detection: The community notion in traditional social networks was associated to a nodes group with more important internal links than external links. Then in OSN, this notion was extended to users group having the same interests and interact more frequently together than with external users (Nguyen *et al.*, 2011). The objective of the community detection is regrouping nodes having the same semantic context (having a minimal semantic/structural similarity) in the same community. The process aims identifying persons having common characteristics to deduce trust relationships or possible links and respond to other objectives like recommendation. There are five approaches.

Reusing and adapting clustering technics by homogeneity or modularity maximization: It considers a social graph enriched by user's attributes

(Social-Attribute Networks). The process begins with initial clusters (each cluster having a unique node) and then, calculating iteratively the homogeneity/modularity between each clusters pair and regrouping the nearest clusters (Meftahi and Saidi, 2013; Arab and Afsharchi, 2012; Dang and Viennet, 2012).

Reusing and adapting clustering by partitioning technics: There is two demarches. The first one aims partitioning the OSN into K dense groups the most similar users. It adapts an iterative process partitioning at each step the groups obtained in the precedent step to maximize the internal similarity and minimize the external one. The second demarche principle is partitioning the OSN into groups with the more similar K persons. It's based on an iterative process enriching at each step the minimal groups candidates until obtaining groups with the more similar K persons. The two demarches exploit the semantic similarity (Zhou *et al.*, 2009, 2010; Davoodi *et al.*, 2012; Dong *et al.*, 2011).

Using the clustering by oriented interactions regrouping technics: It regroups the most interacting users between them. There are two demarches. The first one operates by transforming the social graph G into a Line Graph G', the G links become the G' nodes and the G nodes become the G' links and then regrouping in G' the similar nodes (relationships) and finally replacing the each according relationship by its both members allowing a user to belong to different groups. It's essentially used to detect fuzzy communities. The second demarche is founded on rules defined to guide community detection. The process begins by identifying a semantic relationship between two users and then, per the defined rules, verifying if the relationship imposes their regrouping in the same community or not (Palla *et al.*, 2005; Evans and Lambiotte, 2009; Tang and Liu, 2008; Cai *et al.*, 2005; Yoshida, 2012; Sun *et al.*, 2009; Qi *et al.*, 2012; Zhou and Liu, 2013).

Using the clustering by oriented contents regrouping technics: It regroups the OSN users based their shared contents. The hypothesis is that two similar users share similar contents. The process calculates the shared contents similarity to regroup the contents the more similar in the same group and then identifies for each user his groups (a user belongs of each group of his shared contents) (Huang and Yang, 2012).

Using the clustering by oriented trust regrouping technics: It exploits the trust notion to regroup the OSN users trusting each other in the

same community. The process estimates the trust inter-users to identify communities (Adali *et al.*, 2010).

Link prediction: The link prediction aims analyzing the topological network actual state to predict the eventual connections appearance/disappearance in the future. While the semantic prediction links explores the OSN using semantic web technics for the same objective. The objective is suggesting new connections between OSN users recommending contents and characterizing the relationships (Gong *et al.*, 2012). There are many approaches.

Exploiting the sociology notions: Per sociologies those notions encourage the relationships establishment between users. The first notion is the hemophilia giving the hypothesis that similar users assemble. This hypothesis exploit the similarity between profiles and interests (semantic similarity), the structural similarity and the structural-semantic similarity to recommend new links. The second notion is the social balance designed also by the triadic closure, giving the hypothesis that friend of my friend are also my friends. This hypothesis allows recommending to a user the contacts of his direct contacts (Akcora *et al.*, 2013; Eagle, 2008; Crandalla *et al.*, 2010; Weng *et al.*, 2013; Gong *et al.*, 2012, 2014).

Exploiting contents or interest's semantic similarity: Calculating similarities between users or shared contents to infer new links between contents or between users and contents. It's identifying users having similar interests to recommend them their similar preferred contents or identifying similar contents to recommend, per example, inter-contents co-citations (Popescul and Ungar, 2003; Parimi and Caragea, 2011; Rawashdeh *et al.*, 2013; Schifanella *et al.*, 2010; Aiello *et al.*, 2012; Chelmis and Prasanna, 2013).

Analyzing the interactions nature and frequencies: Identifying evaluations interactions and calculating those interactions frequencies from two different users concerning the same objects and the trust core between them to deduce eventual conflicts based on their agreements/disagreements score and to weight the relationship based on their agreements/disagreements score and their trust score. If agreements>disagreements and the trust >0 then, the relationship is strong (Leroy *et al.*, 2010; Xiang *et al.*, 2010; Leskovec *et al.*, 2010; Symeonidis and Mantas, 2013; Javari and Jalili, 2014; Cai *et al.*, 2012; Tang *et al.*, 2011, 2012). Table 1 resume all the cited indicators.

Table 1: Indicators synthesis

Indicators	Used information
Structural similarity	Contacts
Semantic similarity	Profile property (age, gender, sexual orientation, religion, political orientation, city, country, etc.)
Structural-semantic similarity	
Predominant sentiment	Container (social group, social page user home, channel video, forum, blog, mailing list,
trust/popularity	scientific journal, digital library, questions/ responses site, etc.)
Interaction degree	Tag
Implicit trust	Topic
Explicit trust/Inferred trust	Interaction (share, citation,cco-citation, evaluation inferred trust (like, dislike), comment, response, visit,
Influence/conflic	subscribe, unsubscribe, trust, distrust, recommend, manage privileges, etc.)
Agreement	Person
Disagreement	Declared trust
Fidelity	Security profile
Reputation	Security group
Relationship weight/Spam/spammer	Privilege (see, modify, share, comment, modify privileges, etc.)
Visibility level	Skill
Pirated account	Project
Indirect relationship expertise	Content (scientific paper, post, image, video, private message, etc.)
professional link/(collaboration, coauthoring/co-citation, etc.)	

CONCLUSION

In this study, the OSN analysis identification process studied a documents corpus composed by 149 documents repartitioned on the different analysis.

From the study presented in this study, it's possible to note that the different approaches, studied in this context, use approximatively the same indicators.

Let's remember that this study final objective is constructing an application ontology dedicated to the OSN analysis. The carried out study in this study permit identifying indicators and required basic data to compute it. The aim is to have the precomputed indicators ready for the use in the different analysis approaches to reduce the analysis data preparation time. The future works will be dedicated to the application ontology and its benefits to reduce analysis time.

RECOMMENDATION

The recommendation systems aim proposing individual recommendations adapted to the users' needs and preferences. Multiple researches works has analyzed recommendation for different domains like marketing, politics and social life (O'Donovan and Smyth, 2005). Two recommendation approaches classes: based-contents recommendation and based-collaborative filtering recommendation (Ricci *et al.*, 2011). The first-class studies user preferences in the past to propose him similar elements. It's based on a process of three steps (Lops *et al.*, 2011):

Contents analysis: Extracting subjective information (positive and negative sentiments) from unstructured contents (e.g., posts and messages raw texts) or from online evaluation interactions (like/dislike).

Profile learning: Identifying positive and negative sentiments scores expressed by a user for an object.

Components filtering: Evaluating similarities between old interests and the new objects to recommend (Sellami *et al.*, 2012). The second class aims proposing recommendations to a user per his contacts interests. It uses two methods (O'Donovan and Smyth, 2005):

Exploiting similarities between users: Analyzing first the old interests of each user to detect similarities between users and then propose to users the recent interests of their more similar contacts (Suliman *et al.*, 2013; Kadima and Malek, 2013).

Exploiting the declared trust between users to resolve the Cold Start problem (a case of a novel user when it's impossible to analyze his interactions historic). This method can be used in OSN permitting users declaring explicitly trusts scores between users. The idea is to propose to a user his trusted contacts interests (O'Donovan and Smyth, 2005; Golbeck and Hendler, 2005; Haydar, 2014; Xie, 2014).

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