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Modeling Online User Relationships: A Review

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***Abstract*—Social networks, such as Twitter and Facebook have recently emerged to play key roles in crucial aspects of our lives. In this regard, the question of how to model the relationships between users on the online interactive platform has become important because it forms a basis for abstracting a social network using social network data. Furthermore, user to user relationship definition gives a more convinient way to represent tie strength between users. The analysis of the tie strength provides a better way to gauge how important users are to one another.**

In this paper, we conduct a survey on the various approaches that researchers of social network analysis have applied in modelling relationships between users. Several approaches have been discussed and we have pointed out the challenges and benefits associated with some of the approaches. We have shown how the individual relationship models fit into the bigger models of social influence, which is a major subject of research on social networks. Finally we have recommended future research for some areas that do not seem to have been addressed yet.

***Index Terms*—Social Influence, Centrality, Tie Strength, Relationship Modelling, Interaction, Survey**

I. INTRODUCTION

Social Networks are comprised of groups of people connected through federated relationships. Researchers in big data research have shown a lot of interest in social network analysis with a view to getting knowledge and trends through the analysis of opinions and sentiment, as well as the consequent influence of actors in a social network. Among the issues of research in this regard are multi-objective optimization (maximization or minimization) of influence and its application for brand marketing or brand campaigns.

Research on social influence also has other classic applications in everyday life such as sentiment analysis [1], opinion leader determination [2] and detection of terrorist activities [3]. Optimization of influence relies on extraction and selection of key indicators from social network data that can then be used to model a specific task, such as popularizing a given brand or service [4]. None of these tasks is achievable without modelling how users relate online.

Additionally, research on social influence measurement has been performed on two fronts [5]. These are: *prediction based measures* which rely on network structural measures to predict influential users and *observation based measures* that seek to quantify the amount of social influence that a user has over the network. Social influence is closely associated with information diffusion processes, which describe node-to-node movement of information through the network. Formulating a mechanism for diffusion will involve modelling how users relate in the course of information transfer. Kempe $et\ al.$ [6] identified two major information diffusion models, namely, the Independent Cascade Model and the Linear Threshold Model. The Independent Cascade Model traces information propagation as it proceeds from one node to another in the social network. The edge weights represent the probability of information being propagated along the edge. A node can either be active or inactive. A node is said to be active if the node has acted on the information received by it, by 'liking', 'sharing' or 'replying' to it. In the Linear Threshold Model, a node is influenced if a minimum threshold of its neighbors have already acted upon the information being passed, and thus is indirectly influenced. The idea of influence in this case is derived from some kind of flow over the edge which, by interpretation would mean that there is a relationship between the influencer nodes and the influenced nodes. Such a relationship should be modelled for convinient understanding and usage.

There are several approaches that have been used by different researchers to model user relationships on online social networks. The common motivation in each of these works is the need to present user relationships in a manner that can be described, quantified and used to define how online user relationships evolve in the course of their existence. In this survey, we investigate the various ways through which researchers have modelled the relationships between interacting online users. We provide a holistic view of the approaches and methodologies used in modelling user relationships and we make the case that the modelling approach adopted is important in determining how well the parameters of interest are computed through the analysis of the social graph. To the best of our knowledge, there is no survey that has specifically been dedicated to reviewing the various approaches that have been used in modelling the relationship between users on social networks.

The rest of this paper is organized as follows: Section I provides an introduction to the paper and Section II provides definitions for social influence as an important aspect of user relationship modelling. In Section III, we review the different methods and techniques that have been used in modelling user relationships. Finally the paper concludes in Section IV with suggestions on open issues for future research.

II. Definition of Social Influence

Specifically, there are influencers that are focused on benevolent pursuits, while others may be malicious in intent. Each of these categories of influence have specific characteristics related to their role, intention, and relationship with other members of the network. Peng $et\ al$ [7] define social influence as a relationship established between two entities for a specific action. In this case, one entity is said to influence another entity if the former is able to alter the opinion or behavior of the latter through their own actions. From these definitions, it can be stated that social network influencers are users who are conspicuously and consistently active on the social network through interactions with other users.

According to [8], the link strength between two users depends on, among other attributes, the overlap of their neighborhoods, meaning that the larger the overlap between neighborhoods of users A and B, the stronger the ties between the two users, and vice versa. Cercel $et\ al.$ [9] describes social influence as follows: Given two users i and j in a social network, and i exerts power on j, which has the effect of changing an opinion or behaviour on j in a direct or indirect way, then user i is said to influence user j. The exerted power comes in form of social actions of acknowledgement, including likes, replies or sharing of information. Similarly, [10] has defined social influence between two users i and j as the weighted total of social actions performed by user j, being the influenced user, on the social posts of user i being the influential user. Other attributes of social influence, as outlined in [7] include being dynamic, transitive, measurable, subjective, asymmetric and event sensitive. Of these properties, subjectivity is probably more interesting because it tends to justify the idea that the choice of user relationship modelling technique adopted depends on the specific attributes of the user as well as the nature of the interaction. According to Riquelme and Gonzalez [11], there is no agreement on how to mathematically express the relationship strength between two users on an online social network and by extension online social influence. However, there is hardly a survey that has been dedicated to investigate the approaches employed in modelling user relationships on social networks.

III. User Relationship Modelling Approaches

As has been mentioned above, there is neither an agreed, universal definition of what constitutes a mathematically expressed representation of user relationships on the social network nor the parameters for its estimation. Consequently, researchers adopt different approaches and attributes to express and quantify a measure for user relationships on the social network. According to [12], a measure of online user relationship is the kind of information that a model takes into consideration when analyzing user relationships. When modelling user relationships, it is common to construct a social graph, in which nodes represent users and edges represent relationships between the users. This provides a more convinient means of analysing the strength of user relationships in form of node relationships on the graph.

A. Centrality Based Modelling

Centrality based models of node relationships mostly rely on topological elements of the social network such as the position of a node in the network and the network neighborhood structure [12]. The assumption being that if a node is located in an appropriate location in the social network then it could be an influential node. They are mostly used for node-level ranking through centrality measures [13]. Centrality metrics give weight to the number of links that are incident to a node and the position of such a node in relation its immediate neighborhood and the global network.

Centrality based relationship modelling is based on the existence of an interaction rather than the frequency of such interactions. Even then, this modelling approach has been used in [14] where single instances of relationships have been used to calculate influence values for nodes. The major motivation of this model is that local attributes used for defining node to node relationships are less computationally expensive and therefore can be evaluated in a relatively shorter time especially in large networks [13]. In this section we review user relationship modelling in the Degree Centrality and Eigenvector Centrality.

1) Degree Centrality Relationship Modelling: The *Degree Centrality (DC)* models node to node ties through a boolean relationship defined as $\alpha_{i,j} = 1$ if a direct edge exists between node i and node j, and $i \neq j$ otherwise $\alpha_{i,j} = 0$. According to this representation, node relationships are based only on the presence of edges between nodes. The limitation of this relationship modelling is that it tends to ignore attributes that are important in determining the relationship strengths between nodes [13]. The relationship model can then be incorporated into the bigger expression representing degree centrality for usage in different scenarios as given in equation (1), where N is the number of nodes in the network.

$$DC(i) = \frac{1}{N-1} \sum_{j=1}^{N} \alpha_{i,j} \tag{1}$$

2) Eigenvector Centrality Relationship Modelling: Eigenvector Centrality (EC) of a node is a global measure of the extent to which a node is connected to important nodes. Li $et\ al.$ [15] define global influence as the influence strength of a node i over the whole network. This means that the Eigenvector centrality of a node is proportional to a location near the most significant nodes or communities in a graph. Eigenvector Centrality defines an adjacency matrix $a_{j,i}$ which shows the nodes that have a relationship with each other. The adjacency matrix can be defined for a directed graph or a non-directed graph depending on the need. Through the adjacency matrix, it is possible to know which node relates with which other node. However, adjacency matrix does not give room for attributes such as homophily or the evolving nature of the network. The modelled relationship once included in the Eigenvector expression makes a good case for calculating the Eigenvecor centrality as Equation (2) shows, with $\lambda \neq 0$ and E_i being the Eigenvector value of node i.

$$E_i = \frac{1}{\lambda}\sum_{j}^{N} a_{j,i}E_j \tag{2}$$

B. Social Action Based Modelling

The nature of social engagement on the social network platform is such that users exchange information about various aspects of life that are of interest to them. The medium of this exchange is a set of social actions such as posts, comments, likes or shares on posts that have been made by other users. These social actions play an important role in enabling social network users to express themselves. In fact, Yang and Pei [16] suggest that social actions are a good way to build the edge weight between two nodes in a social graph. Accordingly, many researchers have recently used social actions such as likes, tweets, retweets or mentions to define the strength of relationships between nodes within the social network. Most authors, in addition, argue that the more frequent interactions are between nodes, the stronger the ties between them. Li $et\ al.$ [17] used a combination of retweets, comments, mentions and keyword similarity to model node to node relationships. While using social actions as a basis for the definition of node influence, this work expressed the strength of the ties as a result of the cumulative social actions taking place between a pair of nodes. In [18], a hybrid of both the context and the content aspect of the network is used to define influence. The content property of a network deals with the type of interactions such as comments and likes that are being exchanged between the users while the context aspect is represented by the topological attributes of the network such the commonality of the neighbors. Sheikhahmadi $et\ al.$ [19] proposed a node to node relationship modelling based on the number and the type of social actions in building the edge weight. To build an edge weight in the graph, they used three metrics of interaction namely number of followers, retweets and comments. In [11], active users have been described as network users who are able to maintain their participation in the network in a manner that is constant and frequent for a period of time, regardless of whether they receive attention for their participation. In this work, the relationship strength between the nodes has been expressed in terms levels of node activity based on the number of social actions that have been carried out by a particular node.

Azzouzi and Romdhane [10] propose a model that considers social actions such as retweets, replies and favorites in twitter in modelling edge weights. They associate each social action with a weight in the range [0,1] to emphasise the different levels of importance when used in online networks. In their model, a node i is said to have a relationship with another node j, that is $w(i,j)$, if the posts of node i elicit reactions in form of replies, retweets, likes or mentions from node j. Therefore, the relationship strength between the nodes i and j is computed based on the weighted summation of the social actions that node j has generated in response to the posts by node i as expressed in equation (3). In this case, n_i is the number of published contents by node i, $n_{aj}(i,j)$ is the number of social actions a_j performed by node j on the published contents of node i and μ_i is the the weight associated with each social action.

$$w(i,j) = \frac{\sum_{i=1}^{m} \mu_i \times n_{ai}(i,j)}{n_i} \tag{3}$$

A model known as *PHYSENSE*, proposed in [20], is anchored on an idea called activity potential. The activity potential of a network user refers to the total probability of the user engaging in activity on a given topic at a given time. User activity is divided into intrinsic and influenced activities. An intrinsic activity being an activity that shows that the user is not susceptible to interpersonal influence, while influenced activity is the state of choosing to be influenced by each of the connections according to certain conditional probabilities. User activity is measured as the number of own *tweets, replies, mentions, retweets, shares, likes or comments*, respectively. Edge weights are built based on high conversion rates on the activity of influence rather than just the amount of activity. Therefore, to model the relationship strength between the nodes, the authors use the expression in equation (4). In this model, CF_{ij} is the fraction of tweets from user j retweeted by user i.

$$w_{ij} = \frac{CF_{ij}}{\sum_{j \to i} CF_{i}j} \tag{4}$$

In [21], a social graph is created from a network of smartphone communications, and node to node relationship has been abstracted based on the number and frequency of messages exchanged amongst users. The edge weights denoted, denoted as $w_{ij}(t)$ indicate the intensity of message exchanges between nodes i and j at time t. In order to account for possible spamming effects, a threshold value of the bi-directed edge weight is usually considered, that is,

$$w_{ij}(t) = min\left\{C_{ij}(t), Cji(t)\right\} \tag{5}$$

where, $C_{ij}(t)$ denotes the number of messages sent from node i to node j i.e the tie strength between the nodes.

A common concern for researchers investigating user interaction modeling is the high computational overhead that comes with the re-computation of cumulative interactive social action effects, especially in dynamic networks [22]. Secondly, as observed by Zhiyuli $et\ al.$ [23], social networks are inherently hierarchical. This means that the strength of influence along a path that connects any pair of nodes fades with additional hops.

C. Modelling Based on Information Propagation

Modelling of node relationships under the framework of information propagation provides representations on how information moves from one node to the other. Since propagation is a dynamic process, the idea is to express this relationship in a transient manner. As observed by Silva $et\ al.$ [24], this kind of relationship modelling plays a major role in popularizing information through diffusion. The concept of information propagation and engagement power can be used to quantify the activity of a node within its neighborhood. According to Al-garadi $et\ al$, [25] information propagation is the ability of a node to consistently post contents that compel its neighbors to share further down in the network. Engagement power describes the ability of a node to share contents that evoke reactive tendencies among its neighbors.

1) Modelling with Independent Cascade Model: In the *Independent Cascade* model, the modelling of node relationships is done when each edge is associated with a probability of infection which can be assigned based on the frequency of infections, geographic proximity or historical infection traces [26]. An activated node infects its neighbor based on its infection probability assigned on the edge connecting with the neighbor. In each step $l \geq 1$, each node activated in step $l-1$ has a single chance to influence its inactive out-neighbor, j with an independent probability pr_{ij}. According to general cascade models, when a node i attempts to activate another node j, it succeeds with probability $pr_j(i, S)$, where S is the set of neighbors that have already tried to activate j, and failed. The Independent Cascade Model is the special case, where $pr_j(i, S)$ is a constant $pr_{i,j}$, independent of S [6]. Information propagation process usually terminates when there are no more new nodes to activate.

2) Modelling with Linear Threshold Model: Under the Linear Threshold model, a node j gets to select a uniformly random threshold influence value θ_j, which is in the interval [0,1]. At each time step t, where H_{t-1} represents the set of nodes that have been activated at time $t-1$ or earlier, each inactive node becomes active on condition that:

$$\sum_{i \in \eta^{in}(j) \cap H_{t-1}} w(i,j) \geq \theta_j \tag{6}$$

where, $w(i, j)$ is the modelling for the relationship between nodes i and j and η^{in} is the set of incoming edges. Although in most cases a diffusion probability is assumed, there are studies that have proposed the computation of this probability [27]. Similarly, this model relies on probabilistic approximations of node-to-node relationship strengths.

D. Homophily Based Modelling

Homophily is the tendency of users in a social graph to form associations with others based on certain attributes, such as gender, race, occupation or political views [28]. Specifically, a pair of users is said to relate through homophily if one or more of their attributes match in a proportion greater than other relationships within that network. Homophily may be defined from both a static and dynamic perspective. Static homophily exists when node attributes do not change over a finite time period, while dynamic homophily occurs when node attributes change frequently, or are time-dependent. According to Zardi $et\ al.$ [29], the edge weight in static homophily is increased by a fixed factor σ that represents the importance of the associated attribute as,

$$w(i,j) = w(i,j) + \sigma_{att(ij)} \tag{7}$$

where, $att(ij)$ represents a node attribute and $w(i, j)$ is a measure of the relationship strength. Homophily provides an attribute based relationship building model in the social network. When intensity and frequency of interactions is given consideration, the edge weights increase or decrease depending on the frequency and intensity of their interactions.

In order to model node relationships, Chen $et\ al.$ [30] use both reply relationships and the time at which users are making posts on the social network. A reply relationship is established if two users reply to the same post, With the edge weight being built as,

$$w(i,j) = \begin{cases} \frac{sim(i,j)}{|T_i - T_j|},\ if\ \ T_i \neq T_j \\ sim(i,j),\ if\ \ T_i = T_j \end{cases} \tag{8}$$

where, $sim(i, j)$ is the Jaccard Similarity Index between the adjacent node set of nodes i and j.

E. Topic and Opinion Based Modelling

Online discussions are always on a variety of topics that trend from time to time. A trending topic is one that attracts a large number of opinion expressions from users. The abstraction of relationships between nodes is therefore based on the content of topics shared by users. This abstraction relies on topic contents and the kind of interest that such topics generate from other users. According to this approach, user relationships are built on the basis of topical interests or similarity of topic interests. According to [11], unlike most models that use only relational interactions among network members, this abstraction approach models relationships by analyzing the content and similarity of the information shared among members of the social network. The abstraction uses subject topics as their main approach to graph abstraction.

Bogdanov $et\ al.$ [31], proposed a model called genotype, through which they were able to summarize a user's topic-specific footprint in the information dissemination process in relation to what another user is posting. In this model, a user's topic distribution is monitored based on their interest in Twitter's topical hashtags. To determine the tie strength between two nodes, an edge $e_(i, j)$ is modelled between a followee i, who has adopted at least one hashtag h within a topic T_i before the corresponding follower j. The weight of the edges is determined by the number of hashtags adopted by the followees.

IV. Conclusion and Recommendations

In this survey, we have provided a summary of approaches adopted by various researchers for building and modelling relationships between users on the social network. We have argued that in order to model a social network, it is important to get right the modelling of user relationships. Through the modelling of user relationships, we can then mathematically formulate expressions for the edge weight i.e the tie strength.

The approaches that have been reviewed in this paper can be categorised into three general groups - those that represent user relationships as simple link based relationships that do not take into consideration the frequency of interaction between the users, those that base the formulation of relationship strength on the content and frequency of interaction together with other attributes and the approaches that tend to combine the first and second categories.

Finally, there appears not to be works that build user relationships based on semantic analysis of the content that is being exchanged among the users during online interactions. As an open issue in this case, future work should consider building user relationship based on an analysis carried out through Natural Language Processing tools that will help in building user relationships based on a well defined criteria.

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