

Comprehensive Study on the Models of Social Network Analysis

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ABSTRACT: - A social network Analysis (SNA) is the technique which studies the relationship between people and groups, how those relations arise and consequences of the relationships. Social network analysis examines the structure of social relationships in a group to uncover the informal connection between people. Social network analysis is based on an assumption of the importance of relationships among interacting units. This paper provides the survey done on the basis of model available in network analysis and this paper also concentrates on the future trends in research on social network analysis.

Keywords: Social network Analysis, social network models.

I. INTRODUCTION

A social network is an outline produced by an individual called nodes, which are tied by one or more specific types of interdependency such as friendship, kinship, common interest, dislikes, beliefs. Social network analysis examines the structure of social relationships in a group to uncover the informal connection between people. Social network analysis is based on an assumption of the importance of relationships among interacting units. It indicates the way they are connected through different social familiarities ranging from casual acquaintances to close familiar bonds.[1] The social network consists of models and applications and theories which are expressed in terms of relational concepts. With growing interest and increased use of network analysis has become a consensus about the central principles underlying the network process. In addition to the use of relational concepts, we have noted the following as being important: Actors and their actions are viewed as interdependent and not independent, autonomous units Relational ties (linkages) between actors are channels for transfer or "flow" of resources (either material or nonmaterial)

Network models focusing on people view the network structural environment as providing opportunities for or constraints on individual action

Network models conceptualize structure (social, economic, political, and so forth) as lasting patterns of relations among actors. Most recently, SNA has become an important tool for organizational consultants seeking to understand connection between pattern and interactions and business outcomes such as job performance.

II. RELATED STUDY

Hamza Loucif, Abdelhak Boubetra, Samir Akrouf work on "An Experimental Study of the Diffusion Process in the Twitter Platform Using the ICM, LTM, and Bass Models"[2]. They present the overview of Linear Threshold Model (LTM), the Independent Cascade Model (ICM), and the Weighted Cascade Model (WCM) a variant of ICM. The main findings of this study reveal that we can propose a new model as Following Cascade Model. An initial set of nodes to start the diffusion process is the important factor that decides the success or failure of the diffusion.

The author in [3] discuss the spatial and temporal diffusion analysis of events using retweet interaction networks between users. Therefore, spatio-temporal analysis of distribution

of event related tweets on Twitter gives us an insight into the characteristics exhibited by different event discussion phenomenon in social media networks.

The paper [4] “Maximizing the Spread of Information through a Social Network” propose that approximation algorithm can be used to influence the maximization. From approximation algorithm you will learn how to apply the Maximum Estimation (ME) approach to solve the truth discovery problem on Twitter and analyze the integrity of tweets from a real-world case study. Dong Wang, Lance Kaplan, Hieu Le, Tarek Abdelzaher [7] proposed a paper describing a maximum likelihood estimation approach to accurately discover the truth in social sensing applications. Build a ME based tweet trust analysis tool using Expectation Maximization to analyze the truthfulness of reported tweets.

Erick et.al. [5] gives the idea , how the information spread through the network. More particularly, find in which conditions, person forwards information. One of the key challenges is to understand how information diffuse through social networks and what can positively or negatively affect it.

There are both unsupervised and supervised methods for link prediction. Liben-Nowell and Kleinberg [6] survey the unsupervised methods, including preferential attachment , random walk with restart. Unsupervised learning approach provides the various methods for link prediction based on node neighbourhood, ensemble of all paths and other higher level approaches. Finally, link prediction mainly focuses on predicting whether a link will be formed or not without caring about how links are diffused under certain effects, so we can study diffusion mechanism of links.

Learning to predict reciprocity and triadic closure in social networks, T. Lou, J. Tang, J. E. Hopcroft, Z. Fang, and X. Ding [8] authors proposed a how one way and two-way link form in social network. Paper gives unsupervised as well as learning approach to predicting reciprocity and triadic closure in social networks and a learning framework to formulate the problems of predicting reciprocity and triadic closure into a graphical model.

Lars et.al [10] proposed a Supervised Random Walks, an innovative approach for link prediction

and link recommendation by using learning algorithm. By utilizing node and edge attribute information our system guides the random walks towards the desired target nodes & to estimate the strength of social links. Supervised Random Walks are inadequate to link prediction, and can be applied to many other problems that require learning to rank nodes in a graph.

3 Multidimensional Social Networks:

Model 3.1 Multidimensional Model of the Social Network

The expected nature of social network models should reflect interaction between users with respect to the all types of relationship existing between network’s users accompanied by proper description, namely strength and dynamically of relation. The representation of relations in the model should additionally allow gathering customized description to be easily concluded in order to provide informative presentation of networks and individuals characteristics. The general idea behind the multidimensional model of the social network endeavours to provide the framework allowing the description of entirety of social interactions existing between network actors. Multidimensional model of the social network presented in the paper is based on the basic profile of multidimensional and dynamic social networks. The foundation of each social network is a structure made up of individuals, which are tied by one or more specific types of interdependency, such as friendship, kinship, common interest, financial exchange, likes and dislike, etc. In order to represent such entities, the model assumes the representation of nodes and edges, where nodes represent people (social entities) and edges – interconnections between them. Obviously, as there exist multiple numbers of interconnection types, the edges may represent distinct meanings of relation. Therefore, the model assumes they contained in some semantic layer of relations of the same meaning. Social networks usually are not a static structure and may form relations that change over time. Thereby, the set of network actors may vary over time. The dynamics of relations and nodes needs its representation and is modelled by time windows – a set of static pictures (snapshots) representing the state of network obtained in

certain time interval. The proposed model additionally encompasses information not only about dynamite and different kind of relations but also the groups that exist within a given relation layer and in a specific time window. It provides the opportunity to distinguish distinct sets of nodes with high density of internal edges and low density of edges between those sets. Concluding, the general concept of the model considers three distinct dimensions of social networks: layer dimension, time-window dimension and group dimension. All the dimensions share the same set of nodes that corresponds to social entities: single human or groups of people.

3.2 Dimension 1: Layer Hierarchy

Layer dimension describes all the relationships between the users of a system. The relations may represent direct communication between users via e-mail or phone. But they also may result from human activities in IT system, e.g. sharing and co-editing documents in business intranet. In general, three categories of relations are distinguished: direct relation, pseudo direct relation and indirect relation, see [3] for details. A relationship between the users may be directed, when it takes place from one user to another, or undirected if a direction of the relation is not determined.

3.3 Dimension 2: Time Hierarchy

Temporal analysis of social network is possible thanks to time-window dimension. A time-window is a period with well-matched size. It may be a snapshot at given time stamp, i.e. relation existing at that time, but also relations extracted for a given period, i.e. based on human activities within time-window. Time-window limits social network analysis to those users (nodes) and relationships (edges) that have existed in a period defined by time-window size. Resulting social network may be simple (one-layered) or multi-layered. Missing information or changes prediction is then possible by comparing networks from successive time-windows.

Basic problem of temporal SNA is time-window resolution. If time-window is too narrow structural limits of social network are not correlated and the window itself introduces relatively big noise in

parameter values. In turn, too wide time window entails loss of information about temporal dependencies occurring between relations and nodes in social network. To solve this problem it is necessary to apply a method - like presented in [11] - that enables a choice of time-window ideal size. Similarly to layer dimension, time-window dimension comprises time-windows with different sizes, moving windows, etc. that correspond to various Window Schemas.

3.4 Dimension 3: Group Hierarchy

Concept of group is not precisely define in social network environment. In general, it is considered that group assembles similar people. Frequently, instead of definition we can find conditions (criteria) that should be fulfilled for the group to exist. Most of these conditions derive from an idea, that a group is a social community which members more often coöperate within the group than outside. So, in social network context, a group may be defined as a subset of users who are strongly connected with the other members of the group and loosely with members of other groups. In the model of multilayered social network, group dimension is supposed to contain all the social groups possible to get in the clustering processes. However, different clustering algorithms may be applied. Clustering create the second level in the hierarchy of group dimension. In addition, a Parent Group concept is introduced. It is a virtual object - a root of a group hierarchy, which preserves information about inter-group relations used further in the aggregation process. A single social group may include a subset of social network users connected by single relation or more than one relation in a given period. Thus it may be considered as multilayered structure in time-window. A group may also evolve in time. Its temporal changes and their dynamics give valuable information.

3.5 Views – Dimensional Intersection

The dimensionality of the multidimensional model for the social network, which is presented in the paper, is utilized to close the state of the network providing its static picture. Therefore, the concept of views as a core of the model is introduced. The view is a sub-network consisting only of nodes and edges that belong to particular

layer, time window and group. It means that the single view describes the state of the sub-network composed of nodes tied by edges representing the same type or relation between nodes, from the same time and that are in the same group of nodes. Thus, the concept of the model for multidimensional social network may be compared with principal assumptions of logical architecture of data warehouses.

IV. METRICS USED IN SOCIAL NETWORK ANALYSIS

SNA Metrics is one of the most extensive researches in social network and graph representation area. These metrics based on the classical sonograms and borrowed from mathematical graph formula. Some network properties we mention before also actively give in forming metrics criteria. By knowing relations between nodes inside a network, we can calculate varieties useful measures and importantly metrics can show network structures. Having metrics also means we quantify a network and use the measurement for several purposes. Essentially we divide metrics based on the popularity of SNA application in real world, they are centrality and non-centrality. Centrality is widely used in many applications and it measures the degree to which network structures determines the importance of a node in a network [12]. We divide centrality into three parts: degree centrality, between centrality and closeness centrality. Non-centrality metrics are including reciprocity, density, transitively, hemophilia, component, similarity, and signed networks. Degree centrality basic idea is to compute how many edges are tied to a node, with variations on how we distribute score proportionally to their neighbors, how we compute on directed / undirected network, how we rank the importance of node based on in / out-degree. These variations determine the following metrics Eigenvector (and its adaptation called Alpha), Katz, Page Ranks and Hubs & Authority. The complexity of real world networks implicate measuring using degree centrality itself is not sufficient. To complete centrality measures in different aspect we may use between and closeness.

V. CONCLUSION AND FUTURE WORK

Most of the people in recent days use social network to express their views and opinions, share their emotions. So the social media is the place where huge amount of information is published. As a result social media has become an important source of people's opinions. In this paper we studied the diffusion mechanism of links in micro blogging networks. we prove that the "following" links propagate according to the triadic structures with different diffusion strength. For future work, it is intriguing to study other triadic structures in addition to already existing. Designing and implementing randomized controlled experiments would also be an important direction to confirm the casual relationship in the formation of links

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