An Exploration on Social Attributes of Key Players in Dynamic Social Networks

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Abstract

The identification of most the effective individuals in a dynamic social network can be utilized to better understand and control the behavior of network nodes. Since most of real-world social networks have social characteristics and time-varying features, it is non-trivial to study the importance of social attributes of individuals on the key player identification problem. In this paper we investigate the inter-relationship between some important social features such as the flexibility and sociability of individuals with the importance of their roles in dynamic social networks. Particular applications are used for information diffusion through the network. To this end, a dynamic network model was designed to provide definitions for individuals' social attributes, and describe opinion transfers between them. By means of simulations, the effectiveness level of various sets of individuals in information diffusion is investigated. By selecting sets of players from different regions, the relations between these social features and the importance of the individual's roles are revealed.

Index Terms—Dynamic social networks, Key players, Social attributes

I. Introduction

Modern networks have played important roles in the development of our world. The spread of information through the internet, ubiquitous mobile communication networks, and expansion of online social networks have become essential parts of our society. In the realm of scientific research, the emergence of online communities, document archives and databases, and *crowd sourcing* research projects can be accredited as examples of incredible advantages of modern networks in the development of human knowledge. Online financial networks, online shopping and trading agencies have also deeply influenced world economics. Therefore, developing methods to analyze social networks have become a very important and necessary line of research in recent years. Extracting knowledge from observations of social networks can have direct advantages in various fields such as organizational management, finance and economics, social and political analyses, education and research services, medical and psychological projects and fighting crime and terrorism. For the purpose of this paper, 'knowledge extraction from networks' refers to the process of identifying sub-communities within the network [1]-[4],in accompaniment to the identification of the most influential and effective nodes [5], [6], evolution patterns of the network [7]-[12], etc.

Identification of the most effective nodes, which is termed the Key Players Problem (KPP), is one of the lines of research in social network studies, in which one attempts to identify a set of nodes with the most positive or negative effects in the networks. By positive effects one usually addresses the influence a node has in the spread of information through the network. As for negative effects, one would examine the criticality of the node in rendering the whole network damaged or fractured. As an example of positive KPP, consider the selection of a set of individuals in an organization to handle the task of educating some new protocols to all individuals in the organization. For a negative KPP example, consider the identification of critical individuals in a crime organization in order to cause a collapse of that organization.

General frameworks and methods for the identification of key players in static networks, i.e. networks that their structure does not vary in time, have been studied in several previous studies [5],[13]. The main approach in such an analysis is to define the appropriate criteria of nodes to be key players. Centrality measures [14] can be mentioned as the most popular types of such criteria, however it is argued that they may not be the best choice for all problems on variednetwork topologies [5]. Since the network structure (represented by the graph of the network) is not changing in static problems, the identified set of key players is also invariant and as such the criteria and methods to locate them would be straightforward and based on conventional graph theory. This is not the case for dynamic networks which possess time varying structures. The definition of a key player identification problem should be clarified for dynamic networks: one may be interested in the identification of key players at each time instance or time span, or be interested in the selection of key players for the overall behavior of the network. In an effort to illustrate the contrast of these two aspects, consider a problem of finding the best nodes for routing data in a communication network at each time instance, and on the other hand consider the problem of selecting the best individuals to advertise something in a social network. In the first example temporal KPP is addressed and in the latter case the overall results in a whole period of time are of importance.

It should be also noted that finding the set of key players is not simply reduced to finding a set of nodes which individually have the most effect in a given network. This means that if one finds that nodes*x* and *y* have high scores for being a single key player in the network, it is not generally deduced that the set $\{x,y\}$ would be the set of key players in the network. For example, if the removal of only one node is considered for the fracture of a network and the removal of node x or node y can cause the most fracture, the set $\{x,y\}$ may not be the most effective set in causing network fracture ie. through the simultaneous removal of both nodes [5].

In this paper, the problem of identifying the set of key players in dynamic social networks is addressed with the goal of determining the best spread of opinions in the network. This problem can arise in advertising tasks on social networks or new education protocols in large organizations. Hence the overall behavior of the network in the diffusion of information for an overall period of time is considered. The concern then is to observe how social attributes of nodes can affect their roles within the network in order to determine the set of key players. The social attributes considered in this paper are based on time variations of the nodes; representing *readiness*, *specialty*, *flexibility*, and *sociability* of nodes. The effectiveness of the selected sets of key players in an opinion spread through a network is checked by means of simulating an opinion initiation for a set of selected nodes and observing the final state of the entire network.

The following sections of the paper expound on these concepts in this progressive structure: Section 2 discusses related work which has scrutinized various aspects of social networks, KPP, dynamic networks and their time evolution, and social features of nodes. Section 3 describes the main aspects of the network models considered in this paper as well as definitions utilized, and the methodology of the study. The simulations and their results are discussed in section 4 and concluding remarks are presented in section 5.

II. RELATED WORK

In recent years, social networks have been investigated from various viewpoints, for various goals, and by different analytical methods. Concerning the particular focus of this paper (Key Player Identification Problem), the previous literature is indicative of several research trends. It outlines that research on the Key Players Problem in social networks can be divided into four main categories. The first type of research includes attempts to define more appropriate and useful metrics/criteria for quantifying the importance of the roles of individuals in a network. It is necessary to compare different sets of players in order to find the *key set* among them. The definition of such criteria often transforms the KPP into an optimization problem, for which the solution is the set with maximized or minimized value of the established criterion. The criterion selected for being a Key Player may be different based on the specific objective. Another avenue of research concerning KPP, encompasses the *methods* used to find the set of key players, such as solution algorithms regarding optimization problems (defined by criteria described in first line of research). Finding the exact key players set could be often very hard and a time consuming search problem, specifically for large networks. Therefore, one needs to devise and utilize more efficient algorithms to obtain the solution of KPP. A third aspect covers the applications of KPP identification. The fourth category of research efforts in this field concerns generalizations and extensions of the problem. The generalization of the problem for dynamic and time varying networks, and also the extension of utilized data from the network containing social attributes of individuals can be mentioned. In this section, previous research and review these four approaches of research in KPP is addressed.

The most simple and basic approaches define and quantify the importance of nodes are based on centrality measures [14].The most familiar centrality measure is the degree of nodes. This, however, does not contain information of the network's global structure or interconnecting pathways. The metrics such as betweeness [15], [16] and Katz centrality [17] have been devised to further refine the concept of centrality. Centrality measures in social networks have been reviewed in previous work [18]. However, centrality measures may not be the best criteria for assessing the importance of nodes for information diffusion (positive) or network fractures (negative) in the context of KPP. Various problems of key player identification in static networks have been addressed in [5] It is shown that, based on the goal of any particular problem, the metric used for a set of nodes is particular to that problem. Several metrics for the assessment of key players in positive and negative KPP are also proposed in [5].

In other works, metrics of nodes' importance are defined based on theoretical information approaches [19]. The effects of removing nodes on the entropy of change on the network have been used to measure the importance of the nodes [19].

The search for multiple key players on large networks can be computationally challenging. It has been discussed that the search for k critical nodes from a general graph has the complexity of NP-complete [7]. However, it has been shown that tree graph problems with uniform costs for all links, can be solved in polynomial time, despite the fact that general tree problems have a time complexity of *NP-C* [20]. Several greedy and heuristic algorithms have been proposed in the literature in order to solve KPP [21].The joint consideration of nodes' importance metrics and the KPP solution methods in several works has been addressed. There are two metrics for network fragmentation; one based on the remaining component size and the other is based on the total pairs of mutually reachable nodes. These metrics have been utilized, as in [22], and the computational time for the exact solution of KPP is reduced via a novel compact formulations the problem.

In the realm of applications, KPP analysis has been used to find several key targets in the network of child exploitation websites [22]. A measure which combines the severity of contents and the connectivity of the website is shown to be more appropriate in that application [23]. Contextual effects within the criminal networks are investigated by means of game theoretical methods [24]. This game theoretical idea has been also extended and utilized in real circumstances [25]. Heuristic methods are proposed in [26] for preventing contagious information to be spread through networks (negative KPP). These methods are also tested on real datasets such as Wikipedia network.

The KPP in dynamic networks is more challenging than in static networks and in recent years has attracted researchers' attention. The change caused in the network after removal of several nodes has been addressed in [27]. It is proposed that the potential substitutes for disappearing groups have to be formed between homophile nodes. A change detected in terrorist networks, which has been one of main concerns in KPP studies, has been addressed in [28]. Particularly, in that research the main goal of change detection is set to observe the effects of events such as capturing leaders. In [6], temporal centrality metrics are used in order to identify most effective nodes in a dynamic social network.

Other aspects of KPP in social networks have been considered for generalization and extension of research. Incorporating social attributes into the problem is one of the most important aspects of implementation. Some of social features in networks are reviewed in [29]. The effects of social features on information routing in networks have been studied by several researchers. A Routing algorithm based on the friendships between nodes is proposed in [30], in which a metric for determining friendships in network is also introduced. Friendship relation models are yet to be developed in more sophisticated ways, as friendship has its inherent complexities and non-uniformities in a social network. By means of Bayesian modeling, the influence structure of unequal friendship connections is studied in [31].

III. MODELS AND DEFINITIONS

In this section we describe the core principles of our dynamic social network model, the problem statement of Key Player set identification, definition of social attributes, observations, simulation and analysis. As mentioned earlier, this paper proposes to distinguish the set of Key Players which are responsible for the most effective information distribution within the network based on the social dynamic factors. This means that the KPP addressed herein is of a positive type and non-instantaneous. Several social features for the nodes in the network which may be varying with time, including readiness and sociability of the nodes are defined. These are extracted from observing the variations in the structure of the graph of the network. It also includes flexibility and specialty of the nodes, which are extracted by observing the attitudes of individuals. Therefore, we assume that it is possible to define attitude tags for the individuals in a social network which may be present in real world networks in the form of information on individuals' interests, transactions or activity profiles.

In this section, first we present the essential definitions of our dynamic social network model. This is followed by a problem statement for the identification of Key Players in a dynamic social network, and the manner in which the measure the quality of information spread through the network by simulation is introduced. Social features which are used to analyze the behavior and roles of the individuals in the network are further defined.

A. Dynamic Social Network Model

The basic model and definitions used to term the dynamic social network are described in this section. The instantaneous structure of the network is represented as a graph containing a set of nodes (vertices) V, and a set of edges, E. Different terms are used to contrast between all possible entities in the network and the corresponding presence of each entity at an instance in time.

Definition 1.Universal Network: The term universal network is utilized to address the set of all possible individuals and contacts between them. The notation used for universal network is $U = (I, L)$, in which I is the set of all individuals (players) in the network, and $\mathrm{L} \subset I \times I$, which is the set of all possible links between all individuals. Therefore, a player and a link may either be present or not at any given time.

Definition 2.Instantaneous graph of the network: At each time instance, depending on the presence of individuals and links or their absence, there is an instantaneous graph for the structure of the network which is shown by, $G_t = (V_t, E_t)$, in which V_t is the set of vertices present at time *t*, and E_t is the set of edges present at time *t*. We have $E_t \subset V_t \times V_t$, $V_t \subset I$, $E_t \subset L$. The terms, *nodes* and *edges*, are used for instantaneous graphs to contrast with terms *individuals* and *links* for the Universal Network.

Definition 3.Attitudes: For each individual $i \in I$ at time$t$, we define an attitude array $A_t^i = (a_t^{i,1}, a_t^{i,2}, \dots, a_t^{i,m})$ to represent attitudes of individuals (eg. interests or activities) regarding m subjects. Each element in this array, $a_t^{i,j}$, shows the attitude concerning a subject, and may be stored in various data-types (integer, real, string, etc.). However, in this paper we assume integer values represent attitudes of varied levels of individual interests. The attitude array of each individual may vary with time. The manner in which the array may change shall be be described in section 3.3 during a discussion of *flexibility* of individuals.

Definition 4. Opinion: An opinion is defined by a value ω_t^i regarding a subject as possessed by individual, i, at time, *t*. The value of an opinion held by an individual may also vary with time, and its variation dynamics is discussed in section 3.3. An example for an opinion in the real world can be the level of interest of a new product or a law in an organization. This value is considered to be of integer data-type, in this paper.

B. Problem Statement

The aim of this paper is to find the set of Key Players in the Universal Network which can have the greatest effect on information diffusion for a time period. The set $K_n \subset I$ is the set of n individuals which cause the maximum spread and are therefore the key players. It is obvious that a restriction should be placed on the maximum number of selected key players. Each key player's commitment to spread information has a cost, so there is a tradeoff between spreading information and commitment cost. In this study, it is assumed that all individuals incur an equal cost.

The comparison between different selected sets is made possible by quantifying the spread of information. The degree of information spread caused by a selected set$\widetilde{K}_n$is simulated. The degree of information spread caused by set $\widetilde{K}_n$from time $t = 0$ to time $t = T$ is defined by

$$J(\widetilde{K}_n; T) = |\overline{\omega_T^I} - \overline{\omega_0^I(\widetilde{K}_n)}| \qquad (1)$$

in which $\overline{\omega_T^I}$ is the average opinion of all individuals in the universal network at final time T, and $\overline{\omega_0^I(\widetilde{K}_n)}$ is the average initial opinion held by all individuals with selected players set $\widetilde{K}_n$ at the initial time. To calculate the value of J, the network is simulated by initializing a non-zero opinion value to the selected Key Players Set, while the opinion value of other individuals is set to 0. During execution until time *T*, the opinions are shared by individuals and is reflected in their respective opinion values. At the final time *T*, the average opinion value, as held by all the individuals, is measured and the degree of information spread, is calculated.

The Key Players Set, K_n, is the set that maximizes the value of J, provided that the number n is not greater than a limit number, *N*. The KPP is thus formalized as:

$$\begin{cases} \max\limits_{\widetilde{K}_n} J(\widetilde{K}_n; T) \\ n \le N\,. \end{cases} \qquad (2)$$

C. Social Features of Key Players

In this section several social features including readiness, sociability, flexibility, and specialty are defined. These features shall be used to analyze the spread of information through the network by considering the respective effects on key players and other individuals.

Readiness: Readiness is defined as the probability of an individual to be present in the network. If the structure of the network is sampled by time steps of Δt from beginning time $t = 0$ to the final time $t = T$, so there are $M = \frac{T}{\Delta t}$ numbers of observed instantaneous graphs. If the number of graphs containing individual *i* in them is M^i then the readiness is calculated as the estimated presence probability of the individual *i* as

$$R^i = P^i = \frac{M^i}{M}. \qquad (3)$$

Sociability: Sociability feature of individuals represents their level of activity in making contacts to with other individuals. To measure this feature, it is prerequisite to estimate the probabilities of presence of the links in the network. Similar to presence probabilities of players, if the number of instantaneous graphs containing the link $e^{i,j}$ between individualS^i and *j*is $M^{i,j}$ then the presence probability of this link is

$$\pi^{i,j} = \frac{M^{i,j}}{M^i}. \qquad (4)$$

The sociability of individual *i*is calculated by

$$S^i = \sum_{j \neq i} \pi^{i,j}. \qquad (5)$$

Specialty: The specialty is the measure of an individual's attitude deviation from the average attitudes of the all individuals. This feature is calculated as

$$q^i = \sum_{t=0}^{T} \left\| A_t^i - \overline{A_t^l} \right\| , \qquad (6)$$

in which $\overline{A_t^l}$is the average attitude vector of all individuals at time *t*.

Flexibility: Flexibility is defined by the rates of changes in the attitudes of an individual. It can be quantified as

$$F^i = \sum_{t=0}^{T-1} \left\| A_{t+1}^i - A_t^i \right\|. \qquad (7)$$

An important point in the dynamics of information spreading through the network is the way individuals change their opinions and attitudes. Changes in the attitudes of individuals are very complex processes in real world. Therefore, it is necessary to simplify the attitude variation dynamics in order to study the network. Of course there are internal and external sources of such variation. The internal changes in the attitudes are modeled as random processes, and the external sources (by contacts with other individuals) are modeled as functions of relational situations. The dynamics of attitude change for individuals is assumed to be as

$$A_{t+1}^i = A_t^i + \alpha(\omega_t^i)(\omega_{t+1}^i - \omega_t^i) + \sigma_t. \qquad (8)$$

In this dynamics, the attitude vector of individual *i* in a time instance *t+1* is changed from its value A_t^iin time *t*by a random term σ_t, and an external term caused by changes in an opinion value ω_t^i.The function $\alpha(\omega_t^i)$ determines the way the opinion ω_t^i affects the attitude vector. For example, an opinion may change only one of the elements in the attitude vector, and this can be incorporated into the α function.

It remains to model the process for opinion change caused by communication with other individuals. We consider two dynamics for that. In the first assumption (similarity based opinion transfer), an individual accepts the opinion value originating from contact with another individual with similar attitudes (close attitude vectors). This can be formalized as

$$\omega_{t+1}^i = \begin{cases} \omega_t^j, & \left\| A_t^i - A_t^j \right\| < \epsilon \\ \omega_t^i, & otherwise \end{cases} \qquad (9)$$

The relation (9) depicts the occurring process when the attitude vector of individual *j* is closer than a threshold distance ϵ to the attitude vector of individual, *i*, the opinion of *j* will be accepted by *i*.

The second opinion transfer dynamics (familiarity based opinion transfer) assumes that the individual accepts opinions brought by most familiar individuals. The most familiar individuals are ones with higher link presence probabilities to an individual. Therefore, the dynamics assumes

$$\omega_{t+1}^i = \begin{cases} \omega_t^j, & \pi^{i,j} > \delta \\ \omega_t^i, & otherwise \end{cases} \qquad (10)$$

It means that if the link presence probability between *i* and *j* is higher than a threshold value δ, those two individuals are familiar and the opinions can be transferred.

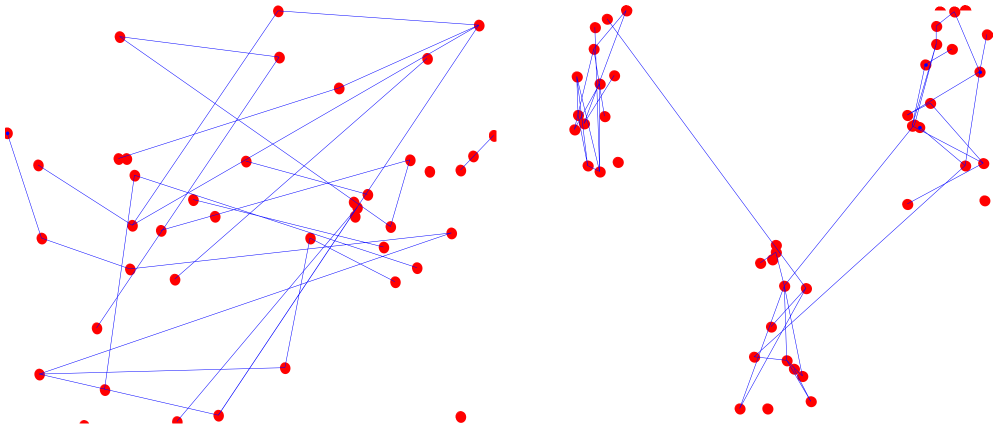
It should be noted that in opinion transfer, the edges of the graph are assumed to be directional, so at any instance in time, one node is transmitting its opinion and the other node of that link acts as a receiver.

IV. Simulation and Evaluation

This section presents the results of simulations in which synthesized data of social networks are produced and the evolution of network is observed. After running the simulation of network evolution, the social attributes of individuals are estimated. The same procedure can be performed for datasets from real world networks.

After obtaining the estimated measures of individuals' attributes, the distributions of their values are investigated. Particularly as the individuals in the planes with coordinates representing the social attributes values are plotted. Furthermore, by clustering the individuals in the space of attributes, one may obtain valuable information about the network and the roles of individuals.

By selecting sets of information advertiser individuals and running the network dynamics for several iterations, the effect of information spread caused by those individuals are quantified by comparing the initial and final status of opinion holding by all the individuals (i.e. by calculating the level of information spread).To uncover the exact key players set, one needs to perform such simulations for all possible combinations of advertiser individuals. However, the number of those possible combinations would be so large in most cases that the exact solution cannot be obtained in a tractable computational time. However, in this study the main aim is to investigate the impact of social relation variables on the diffusion of information by key individuals in a community. Therefore, in the simulations presented here, the sets are determined by the position of individuals in the space of social attributes. This means that each set of individuals is composed of those in a certain region in the attribute space.



(a) (b)

Fig. 1.Examples of instantaneous structures for (a) single community, and (b) multi-community networks.

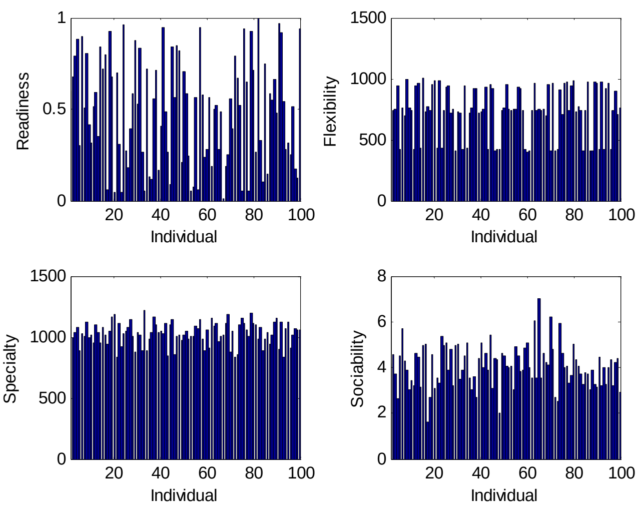


Fig. 2. Estimated values of the four social attributes of 100 individuals in the single community network with similarity based opinion transfer model.

In the simulations, two types of social networks are considered: composed of single community and multi-community network. Typical instantaneous network structures for both types are shown in Figure1.

Based on the type of network (single or multi community) and the opinion transfer model (equations 9 or 10), four different cases of simulation are performed. In all simulations the number of individuals is set to 100, and the number of attitudes (length of vectors A) to 5.

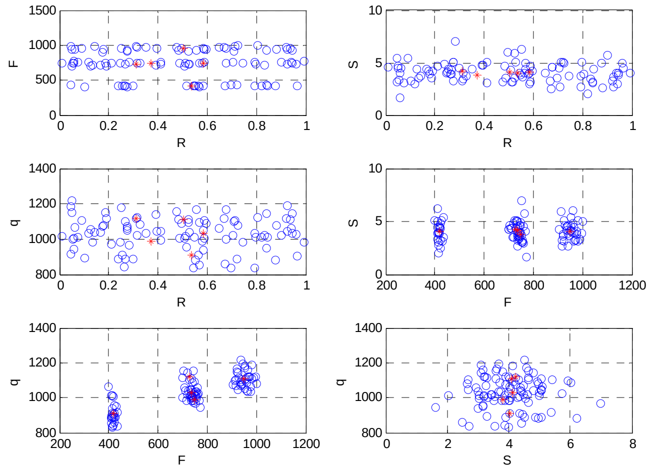


Fig. 3.Representation of individuals in planes of attribute space.

To estimate values of the four social attributes of individuals, random values are initialized for their opinions. In the first case, the single community network is considered to be accompanied by an opinion transfer model of equation 9. For the changes in the attitude vector by opinion transfer (equation 8), the value of one of five attitudes is changed based on the value of transferred opinion. In Figure2 the estimated values of four social attributes for 100 individuals after 300 iterations of network evolution are shown. The positions of individuals in the 6 attributes plane are depicted in Figure3 in which the centers of clusters are also represented by star like markers. It is seen that the flexibility attribute can provide more distinct discriminatory features.

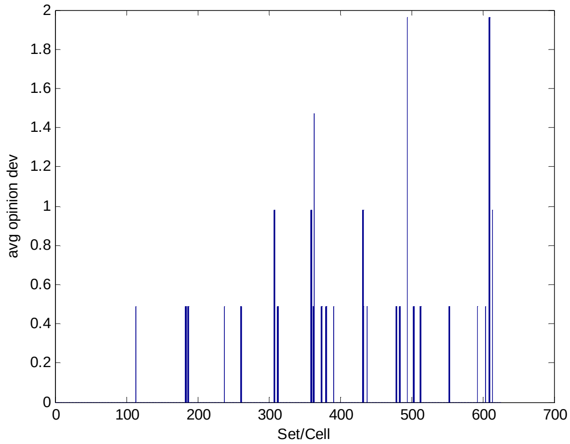


Fig. 4. Deviations of mean final opinions from initial opinions in the single community example with similarity based opinion transfer model.

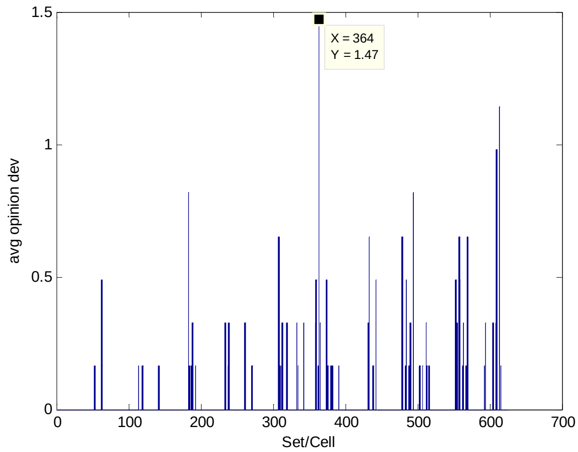


Fig. 5. Average (of 3 simulations) deviations of mean final opinions from initial opinions in the single community example with similarity based opinion transfer model.

To verify the effectiveness of sets of individuals in information diffusion, the 4 dimensional hypercube in attribute space which contains the attribute values of individuals is divided into 625 cells (by division of each axis into 5 intervals). Each cell can then be numbered by four digit base 5 numbers. Individuals existing in each cell form different sets to be verified by their information diffusion effectiveness. Some cells may have no individuals within them, and some may have too many individuals, by more than the allowed limit for key players per set. Those cells are ignored and hence not checked for their information diffusion effects. The results of simulations for checking the effectiveness of opinion spread by the 625 possible sets are shown inFigure 4. In this plot, the vertical axis represents the deviation of the final average from initial average opinion of the network; hence higher values are more desirable. The cell numbers are obtained by transforming the base 5 numbers to their corresponding decimal numbers and adding by 1 (to make it start from 1, not zero). To reduce the random effects in results, the exact simulation is performed three times and the average results of these simulations are shown inFigure 5.

It is observed that the individuals in the cell 364 have the most effect in the information spread. This cell corresponds to the attribute intervals below:

$$\begin{cases} 0.4 < R \leq 0.6 \\ F > 1000 \\ 3.2 < S \leq 4.8 \\ 1160 < q \leq 1280. \end{cases} \qquad (11)$$

This cell contains four individuals which are considered to be the selected key players set. This means that one can select an individual as a key player if its attribute values satisfy relations in (11). The four key players in the aforementioned example are shown in one instant of the network in Figure6 with pentagram-like markers.

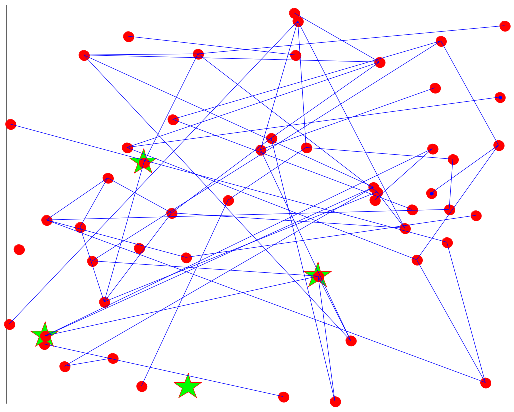


Fig. 6.An instantaneous graph of a single community example with a similarity based opinion transfer model. Key players are shown by pentagrams.

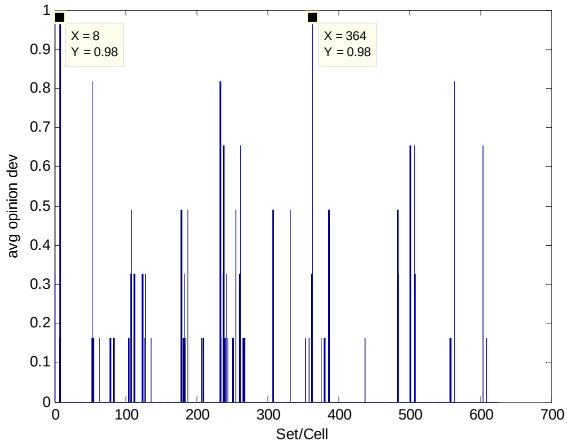


Fig. 7. Average (of 3 simulations) deviations of mean final opinions from initial opinions in the multi community example with similarity based opinion transfer model.

In the second case of simulations, the type of network is multi-community and the other settings are similar to the first simulation case. The results of checking the cells for their effectiveness in information diffusion are shown in Figure 7 in which the average opinion deviations from three similar simulations are plotted. It is observed that apart from cell 364 (which was found in the single community case), cell 8 also exhibits a maximized level of information spread. There is only one individual in these two cells, as such, both are selected as key players in this network example. As shown in Figure 8, both of these key individuals are in a same community. This may be indicative as sign of superior effectiveness of information spread of that community in the network.

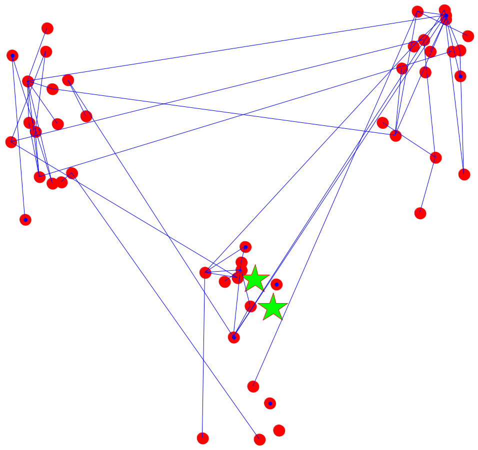


Fig. 8. An instantaneous graph of a multi community example with a similarity based opinion transfer model. Key players are shown by pentagrams.

For the third and fourth cases, the dynamics of opinion transfer are changed to adhere to the constraints of the model described by (10), where the opinion transfer occurrence depends on the familiarity of the two individuals. For the third simulation case, the single community example is used and for the fourth simulation case the three community example is considered. The results for the third simulation case are shown in Figures 9 and 10, and the results of fourth case are shown in Figures 11 and 12. It is observed that change in opinion transfer dynamics has not changed the importance of one of the communities in the multi-community example. However, by comparing Figures 5 and 7 withFigures 9 and 11, it is made apparent that the discriminatory capability of social attributes for key players is higher for the cases with opinion transfer model based on the familiarity (equation 10) than the model based on similarity (equation 9).

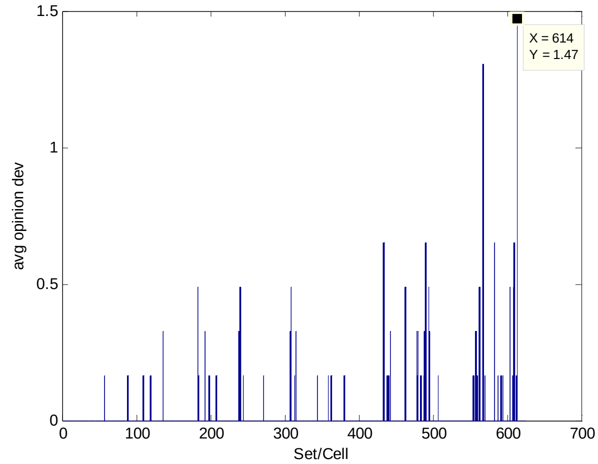


Fig. 9. Average (of 3 simulations) deviations of mean final opinions from initial opinions in the single community example with familiarity based opinion transfer model.

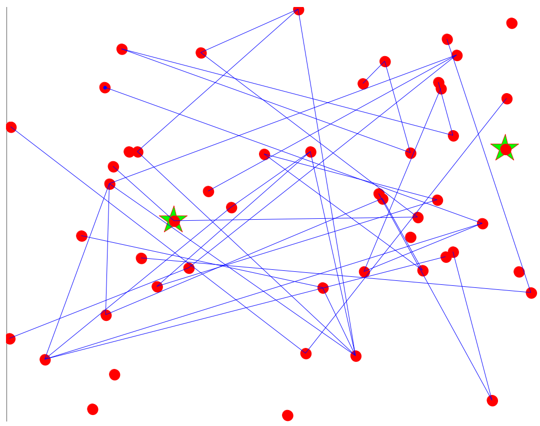


Fig. 10. An instantaneous graph of single community example with familiarity based opinion transfer model. Key players are shown by pentagrams.

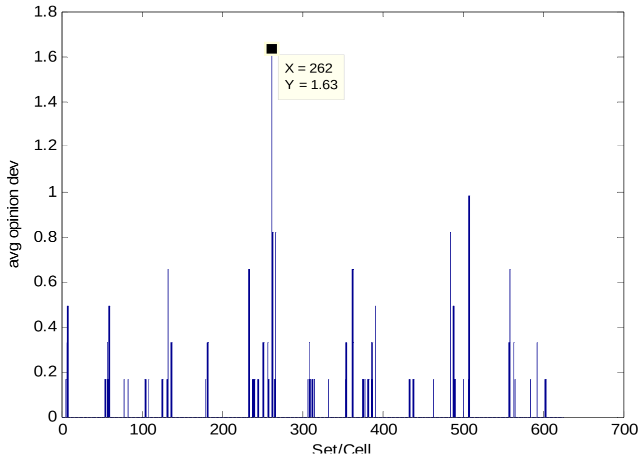


Fig. 11. Average (of 3 simulations) deviations of mean final opinions from initial opinions in the multi community example with familiarity based opinion transfer model.

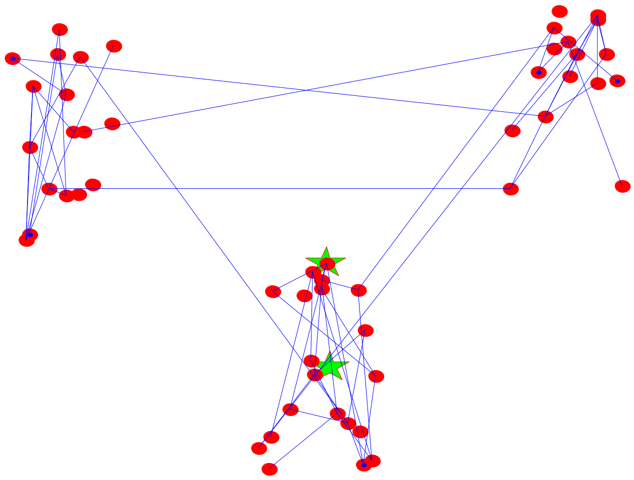


Fig. 12. An instantaneous graph of multi community example with familiarity based opinion transfer model. Key players are shown by pentagrams.

V. Conclusions

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions. In this paper the generalization of the Key Player Identification problem for dynamic social networks is discussed. A thorough analysis of the individuals within the communities was conducted to find the most influential ones in the task of information diffusion through the network, as well as to ascertain the defining social attributes which were utilized. By representing the individuals in the space of these attributes, and dividing said space into several cells, the most effective regions of this attribute space were found. This procedure exposes the social characteristics of the most influential individuals. Then the set of key players are selected from individuals in those effective cells, i.e. the individuals with certain social characteristics. The four social attributes defined for this research are readiness, flexibility, sociability, and specialty of the individuals. It is revealed by several simulations that these attributes can help characterize key players in the network. For simulations, single and multi-community networks were used. Two opinion transfer models, one based on familiarity and the other based on similarity of individuals are incorporated into the simulations. It was observed that in familiarity based opinion transfer examples, social characteristics of the set of key players were more distinct.

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