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The Impact of Structural Position on Opinion Leadership in Social Network

Sajjad Salehi
Electrical and Computer Engineering
University of Tehran
Tehran, Iran

Fattaneh Taghiyareh
Electrical and Computer Engineering
University of Tehran
Tehran, Iran

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***Abstract*— Opinion leaders are individuals who have specific personal features that enable them to impact opinions of other agents named followers. In this paper we are going to introduce an agent based opinion formation model to investigate the impact of structural position of agents on their ability to navigate the opinion of social network. For each agent, this ability is defined based on the judgment of his neighbors about his status. The status of each agent is estimated based on status theory. In proposed model, we suppose each agent can modify the opinion of his neighbors with lower status. By applying this model on two complete and scale free graphs, we have investigated the effect of agents' position on opinion leadership ability. Also the effect of leaders to navigate the opinion of agents is studied. The results of our work can be applicable in competitive environments that different parties try to change the social opinion.**

Keywords—opinion formation, social network, leader, follower, agent

I. INTRODUCTION

Opinion formation is a process by which the opinion of agents about one issue has been changed over time. In this process some individuals might follow others named leaders. Leaders in a social network are people who have strong self-confidence so that they rarely change their opinion about one issue. Because of their acceptability in society, these leaders can play an important role in opinion formation process. Opinion formation models usually focus on three components, agents, relations and process of opinion change. These models consider a graph to model social network so that its nodes represent the agents and its links show the relation between two agents. Each node has a set of variables as features of agents and each link represents the feature of relations in social network. In different models based on their goals, agents and their relations have different features. However all models have a value which represents agents opinion. Also the agents' opinion can be changed in effect of their interactions, external entity like media and so on.

In opinion formation models, agents opinion is modeled by a numeric value that may be discrete [1], continuous [2], fuzzy [3] or a vector [4, 5]. Agents also may have some other features like the conviction power for changing the opinion of others [6, 7], self-confidence [8] and internal opinion [9]. The relation between agents may have different features. These relations may focus only on existence of interaction between agents [1, 2] or consider the strength of impact [3, 8, 10, 11]. These strength can be interpreted as one agent only trust others [3, 8] or may distrust some acquaintances [10-14]. In the opinion formation process some agents might play the role of opinion leaders. Other agents change their opinion based on the opinion of leaders [8]. These leaders can be different with other agents in some features like self-confidence. Also the leader can be different with others in their position in social structure. Current models rarely consider the structure of social network in opinion formation process [15].

In this paper we have considered the agent position in social structure as an ability to make it an opinion leader. We have introduced an opinion formation model considering this ability, named leadership ability. The two measures of generative baseline and receptive baseline introduced in status theory have been applied to calculate the leadership ability [16]. In our model agents with high leadership ability try to convict others to follow them. Agents change their opinion based on the strength of relationship between them. Unlike previous works that consider + and – links as a trust and distrust relations like [10-14], in our model, using status theory, a + link from agent A to agent B shows that agent A believe agent B has higher status while – link shows that agent A believe agent B has lower status. Also agents may change the strength and type of their relations based on their interactions and two mentioned measures, generative baseline and receptive baseline.

The rest of this paper is organized as follows: In the next section, a brief review of previous works is presented. Section 3 explains the Deffuant model while Section 4 provide a description of status theory. Our proposed model is presented in section 5. Section 6 discusses the simulation results of scale free and complete network. Finally, the conclusion and future works are presented.

II. LITERATURE REVIEW

Human behaviors are complex, but simple rules can be generated for interpreting these behaviors in a way that they can be considered as simple automata that response in environment [17]. In this section, we try to express an overall review about opinion formation models in literature. These models can be classified based on their views about society. Some works [1] assume each agent only know two agents in a society. So the social structure can be modeled by a one dimensional lattice. This model may be extended by considering more dimensions. Some works has utilized different types of graph, including complete graph and scale free, for this purpose [15, 18]. Opinion of agents is usually modeled by one variable that may be discrete [1] or continuous [2]. Also intuition from physical science is common in this area. In [19] the temperature is used as a feedback for controlling the process of opinion formation. So probability of modifying the opinion of agents is affected by temperature of community. In other hand, opinion formation with two opinions can be considered as the formation of magnetic that spins turn to one direction and shape a regular formation [17].

An important context for which opinion formation models are suitable is election and selecting a leader [8, 20, 21]. These works usually focus on political applications and consider campaign problem. Campaign problem refers to find a set of people whose positive opinion about one issue will maximize the overall positive opinion for the item in the society. Campaign problem is usually considered in context of election and market [21-24]. Gionis and et al. [21] try to find a set of people to form a campaign and maximize opinion of social network. This problem i.e., influence maximization was formulated by Kempe et al. [24]as a discrete optimization problem. They have introduced three cascade models, namely the independent cascade model, the weight cascade model, and the linear threshold model.

Also selecting a leader to navigate the agents' opinion may be handled by opinion formation models [8]. In [8] Leaders are recognized by personal features like self-confidence. These agents have high self-confidence and high confidence about their opinion so that followers follow them. In other hand, these leaders may be recognized by structural features and position of them in social structure. However structural features of social network are rarely considered in opinion formation models [15]. Jalili [15] considers the social power of agents as an important factor in opinion formation. Also Salehi and Taghiyareh [25] model the opinion formation as a co-evolutionary process. They focus on structural balance theory [26, 27] to engage the instability of social structure in opinion formation process.

As mentioned, in addition to modeling the opinion formation process, relations between agents must be modeled [8, 28]. Förster et al. [28] present an iterative transaction between opinion formation and trust network so that Agents' opinion is modified based on the trust network and trust network has changed by modifying agents' opinion. Recently some works consider the distrust/hostile relations between agents in opinion formation process [10-14]. These relations presented by a negative link in a graph can be interpreted as view of one agent about status of another. Positive link shows one agent believes that other agent has a higher status and negative link shows he believes that other agent has lower status [16]. These works try to investigate the conditions for creating bipartite consensus in social network. While consensus refers to the state that all agents have an identical opinion value, bipartite consensus imply the state in which all agents have a similar opinion value divided in two category with different signs [11]. Also [25] tries to model opinion formation considering structural balance theory. The force of society to change unbalanced relations change the individual opinions. By modeling a social network as a signed graph, more structural features like status theory can be considered.

III. DEFFUANT MODEL

Our proposed model is based on the Deffuant model [2]. This model assume each agent has a continuous value, named x, as opinion that lies in [0, 1]. Also each agent may know other agents in social network or does not. So it models agents with a continuous variable and model social network with a graph that each element is 0 or 1. 1 means agents know each other and can interact while 0 means they don't know each other. Also agents have a confidence threshold u that indicates whether two interacting agents can affect their opinion or not. In this model two

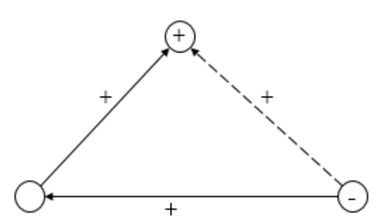

Fig. 1. Predicting link and sign

neighboring agents are selected randomly, *agent i* with opinion x_i and *agent j* with opinion x_j. If $|x_i - x_j| < u$ then agents update their opinion based on Eq. 1 and 2.

$$x_i(t) = x_i(t-1) + \mu\Big(x_j(t-1) - x_i(t-1)\Big) \quad (1)$$

$$x_j(t) = x_j(t-1) + \mu\Big(x_i(t-1) - x_j(t-1)\Big) \quad (2)$$

Where $x_i(t)$ and $x_j(t)$ are the opinion of agents after interaction (in step t) and $x_i(t-1)$ and $x_j(t-1)$ are the agents' opinion before interaction (in step t-1). Also μ determines the rate of change in agents' opinion that can be between 0 and 0.5.

IV. Status Theory

Status theory tries to detect some of the fundamental principles to indicate the link formation in signed social networks. This theory expresses that the opinion of one agent about another can be estimated based on their relationships with other neighboring agents. This theory utilizes a directed signed graph to model the social structure. Each link presents the judgment of one agent about his neighboring agent status. As shown in Fig. 1(a), the positive link shows that *agent 1* (A_1), who generates this positive link, believes *agent 2* (A_2) has higher status. Also the negative link (Fig. 1(b)) shows A_1 believes A_2 has lower status. By considering three agents, status theory tries to predict the sign of potential link. For an example in Fig. 2 three nodes and two links are presented. For each link, a negative sign assigned to in-node and a positive sign assigned to out-

```
Select one agent randomly, named As
Select one of As neighbours randomly, named An
If | opinion As - opinion An | < u
Then
    If the link sign from As to An is positive
    Then
        Change the opinion of As to approach to opinion of
        An
    End If
    If the link sign from As to An is negative
        As suggest that An change his opinion based on
        opinion of As
    End If
End If
If opinion of either agents has been changed
Then
    Update their relations
End If
Decide to change the type of relation between two selected
agents based on their generative an receptive baselines
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Fig. 3. Algorithm for updating opinions and relations

node. So, as shown in Fig. 2, a positive link can be predicted from node with negative sign to node with positive sign.

Leskovec et al. [16] defined two measures for better prediction of agents relations based on status

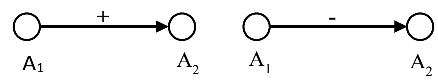


Fig. 2. Positive and negative links in status theory

theory, generative baseline and receptive baseline. Generative baseline for each node is the fraction of out-coming links while receptive baseline is the fraction of in-coming links. These two measure can be interpreted as the tendency of each agent for considering his neighbors in higher status (generative baseline) or the tendency of neighbors for considering this agent in higher status (receptive baseline).

V. Proposed Model

In this section we are going to present our opinion formation model. In this model we try to consider the ability of agents to be an opinion leader. Based on this ability each agent may change his opinion in effect of interaction with others. Also one agent may suggest some neighbors whom he believes they have lower status to change their opinions. The relation network of society may be modified based on the changes in opinions. In other words if one agent interact with one of his neighbors and change his opinion as a result of this interaction, he modifies strength of his relation with this neighbor. Also agents may change the type of their relations (+ or -) based on their generative and receptive baselines and generative and receptive baselines of their neighbors.

Before expressing the opinion formation model, it is necessary that algorithm for managing opinion formation process is outlined. As shown in Fig. 3, one of agents in social network and one of his neighbors is selected randomly. Then Interaction between two selected agents is occurred and agents may change their opinions. So while opinion of one agent has been changed, his relations with other agents is updated. Finally selected agents may revise the type of relation between them based on their generative and receptive baselines.

For updating the opinion of agents we have utilized the Eq. 3. In this step If $|x_i(t) - x_j(t)| < u$ then agents update their opinions. In this equation, $x_i(t)$ is the opinion of agent *i* in timestamp *t*. in each step each agent changes his opinion considering opinion of his neighbor with higher value or suggest the neighbor with lower value changing his opinion. The new opinion of each agent is calculated based on his opinion change (Δx_i). Also for calculating this change the current opinion of selected agent and his neighbor, the strength of link between them ($link_{i,j}$) and the leadership ability of neighboring agent for leading him ($S\_measure_{i,j}$ / $ln(9)$) is considered.

$$x_i(t+1) = x_i(t) + \Delta x_i(t+1) \quad (3)$$

$$\Delta x_i(t+1) = link_{ij}(t) * \left(x_j(t) - x_i(t) \right) * S_{measure_{ij}} / \ln(9)$$

The leadership ability of one agent is calculated based on the Eq. 4. As mentioned in status theory section, two measures, generative baseline (*G_Bl*) and receptive baseline (*R_Bl*), for one node are the fraction of out_coming and in-coming his positive links. So the *G_Bl* can be interpreted as a tendency of this agent to believe that his neighbors have higher status. In other hands, *R_Bl* for one agent can be interpreted as a tendency of his neighbor for believing he has higher status. So we define $S\_Bl_{i,j}$ to calculate the leadership ability of *agent j* for leading opinion of *agent i*. It is the fraction of the tendecy of agent *i* to follow his neighbors plus tendency of other agents to follow the agent *j* and the tendency of agnet *j* to follow others and the willing of other agents to follow *agent i* .

$$S_{measure_{ij}} = \begin{cases} \ln(S\_Bl_{ij}) & if\ 1 < S\_Bl < 9 \\ 0 & S\_Bl \le 1 \\ \ln(9) & S\_Bl \ge 9 \end{cases}$$

(4)

$$S\_Bl_{ij} = \left(G\_Bl_i + R\_Bl_j\right) / \left(G\_Bl_j + R\_Bl_i\right)$$

Fig. 4 shows the values of $\ln(S\_Bl_{i,j})$ on the basis of $(G\_Bl_i + R\_Bl_j)$ and $(G\_Bl_j + R\_Bl_i)$. as shown in this figure by increasing the value of $(G\_Bl_i + R\_Bl_j)$ or decreasing the value of $(G\_Bl_j + R\_Bl_i)$, the value of $S\_Bl_{i,j}$ increases. so by applying this equation, each agent change his opinion based on the leadership ability of interacting neighbor.

In each step if opinion of one agent changes, his evaluation about interacting neighbor will update. Regarding Eq. 5 this evaluation updates based on the change amount in opinion value.

The type of relation that one agent have with other, indicating one agent belives that other one has higher status (positive link) or lower status (negative link), can be changed based on the G_Bl and R_Bl of two agents.

$$link_{ij}(t+1) = \frac{link_{ij}(t) + \Delta x_i(t+1)}{1 + \Delta x_i(t+1)}$$

(5)

$$link_{ik}(t+1) = \frac{link_{ik}(t)}{1 + \Delta x_i(t+1)}$$

TABLE 1. Features of simulated networks

Feature	Scale free	Complete
Total population size	1000	500
Average nodal degree	20	499
Initial opinions	Uniform(0,1)	Uniform(0,1)

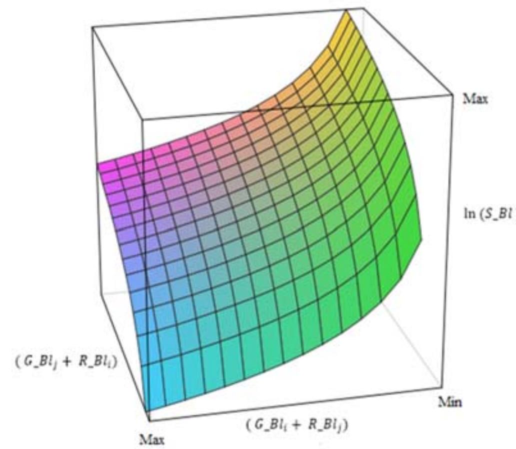


Fig. 4. values of *ln(S_Bli,j)* based on its variables

We expect by changing the type of relations between agents, some ones can navigate the opinions of others based on their position in social network. This ability can be detected based on two expressed structural measures, generative baseline and receptive baseline. In the next step we consider the value of *(R_Bl – G_Bl)* for each agent. This value indicates the ability of agents to affect other agents. So we try to navigate the opinion of all agents to predefined target by modifying the opinion of leaders. If the difference of *R_Bl* and *G_Bl* for one agent is greater than *TL*, the predefined target is considered as a factor to modify his opinion. In other words if *(R_Bl – G_Bl) >TL* for agent i, first his opinion is modified based on the equation 6 and then his opinion may be changed in effect of others.

$$x_i = x_i + sign(target - x_i) * (R\_Bl_i - G\_Bl_i) * 0.1 \quad (6)$$

VI. SIMULATION AND RESULTS

In this section we have presented the simulation results for our proposed model. These simulations ran for two types of networks; scale free and complete. Table 1. Shows the initial conditions of networks. At first we don't consider the ability of opinion navigation for leaders that is modeled by Eq. 6 and evaluate the ability of model to create opinion clusters. Then we ran simulations by considering opinion target and evaluate the power of leaders to navigate the social opinions.

Fig. 5 shows the simulation results of scale free network for different values of u. In this figure horizontal axis shows the steps of simulation and each step shows 1000 interaction in social network. vertical axis shows the opinion values and the color shows the frequency of each opinion value in simulation steps. The color bar presents the map of colors and opinion frequencies. Fig.5(a) presente the distriution of opinions when $u = 0.2$. as presented, individuals shape some clusters in which their opinions are similar. Since the confidence threashold is 0.2, individulas have the chance of interaction with limited rent leaders navigate the social opinions to different points and cause the creation of different clusters. This simulation can represent some social situation like election.

In election different campigns try to attract the society votes by changing their opinions about their popullar candidate. So there will exist several clusters of opinions whith different leaders. Fig.5(b) and Fig.5(c) shows the results for $u = 0.5$ and $u = 1$. In these two samples, individuals have the highier chance for

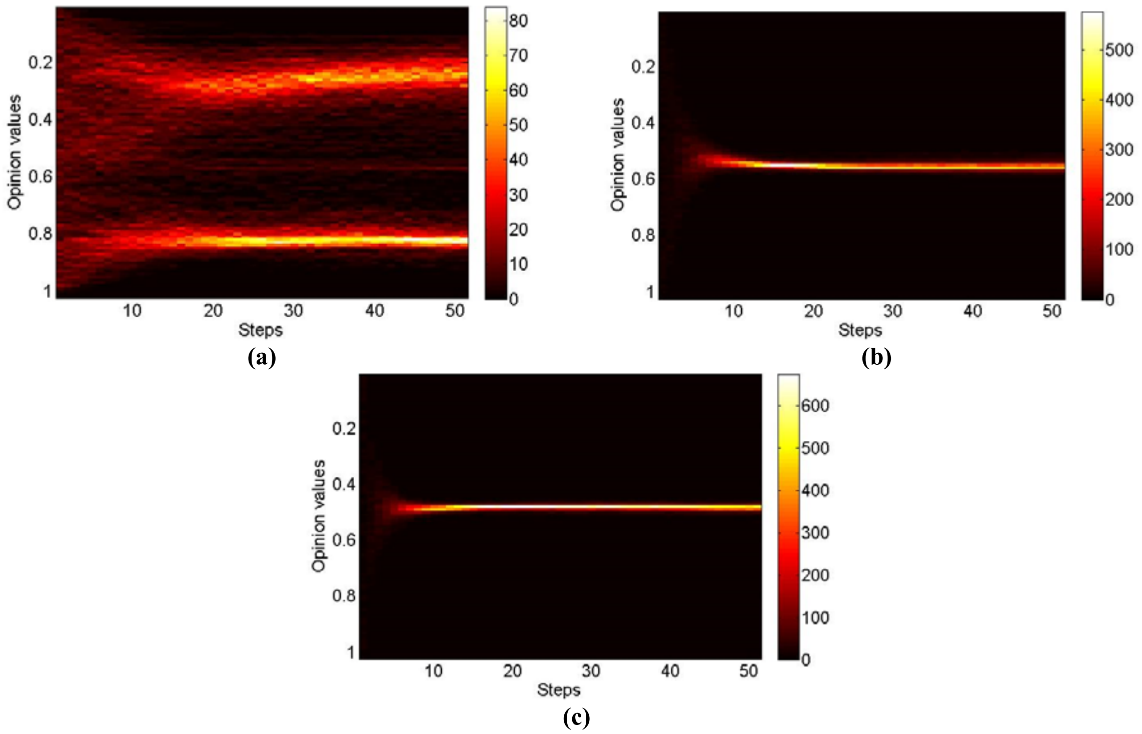


Fig. 5. The simulation results of scale free networks when (a) $u = 0.2$, (b) $u = 0.5$, (c) $u = 1$

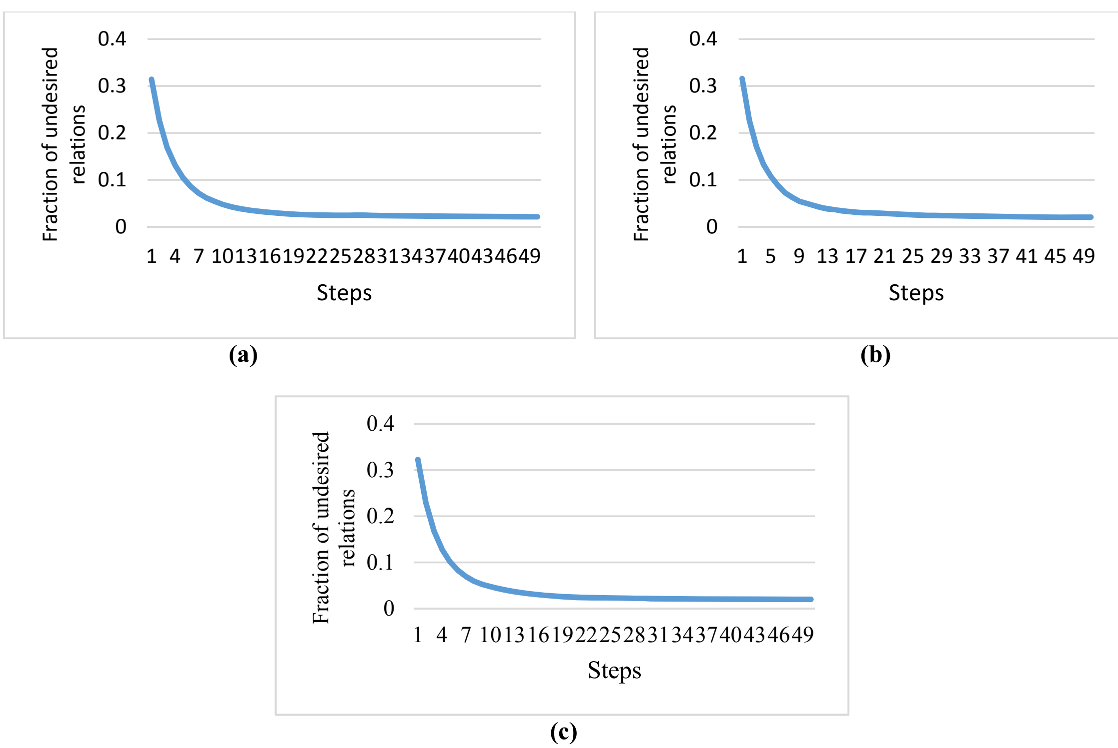
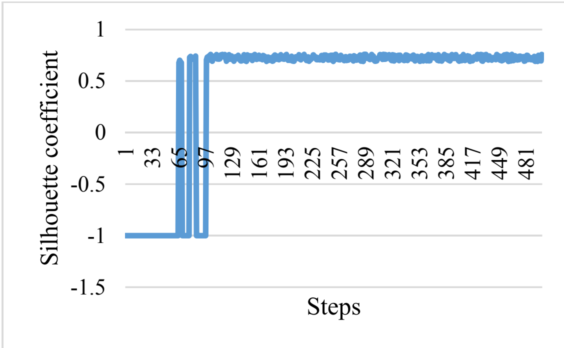
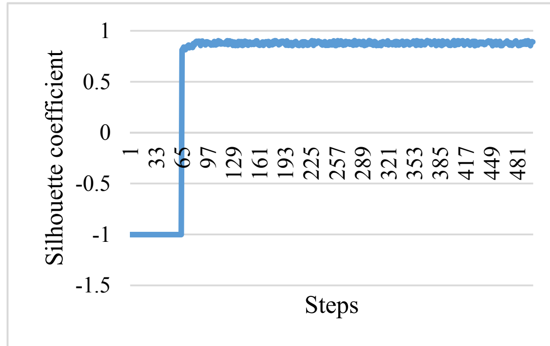


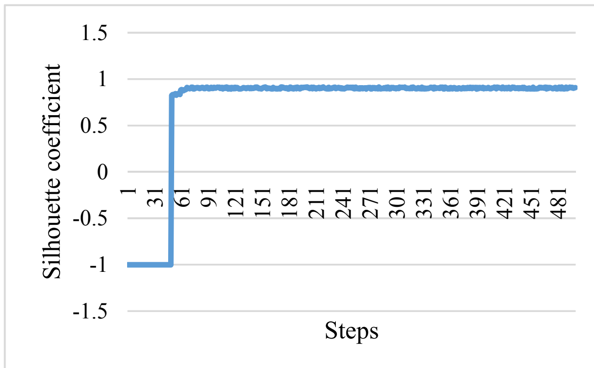
Fig. 6. The fraction of undesired relations in scale free network when (a) $u = 0.2$, (b) $u = 0.5$, (c) $u = 1$



(a)



(b)

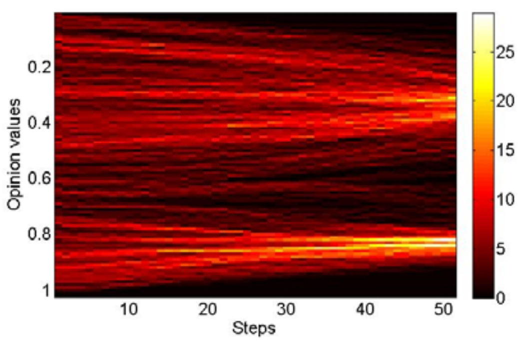


(c)

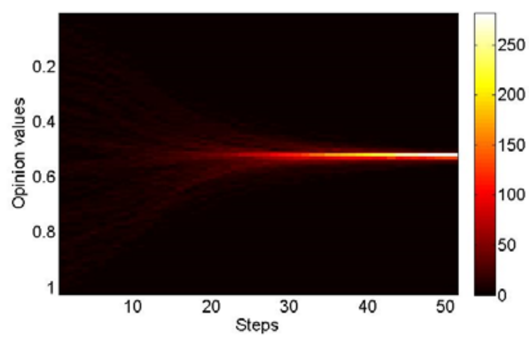
Fig. 7. The Silhouette coefficient value in scale free network when (a) $u = 0.2$, (b) $u = 0.5$, (c) $u = 1$

interaction and so they can reach the consensus. In other words individuals are more open minded rather than previous example and so they are more ready to change their opinions to one point. This can show different social situations like joint decision making.

As mentioned The type of relation that one agent has with other one can be changed based on the G_Bl and R_Bl of two agents. In other words there exist some type of undesired relations that agents try to



(a)



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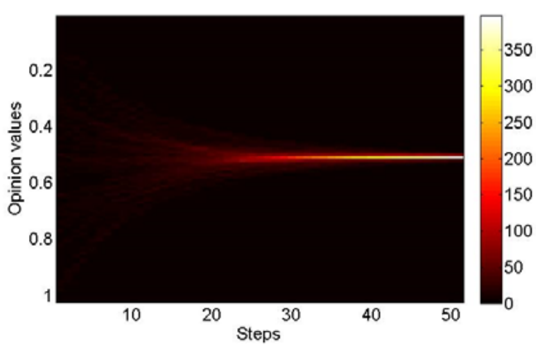


(c)

Fig. 8. The simulation results of complete graph when (a) $u = 0.2$, (b) $u = 0.5$, (c) $u = 1$

change them to desired ones. Fig. 6 presents the fraction of undesired relations in each step of simulation of sacale free network. Vertical axis shows the farction of udesired relations while horizontal axis shows the steps of simulation and each step shows 1000 interactions in social network. As presented, the fraction of undesired relations decreases over simulation for three values of u. but in all samples this value is not equal to 0 at the end of simulation. This shows it is not necessary to change all of these relations to create clusters of opinions or consensus in social network.

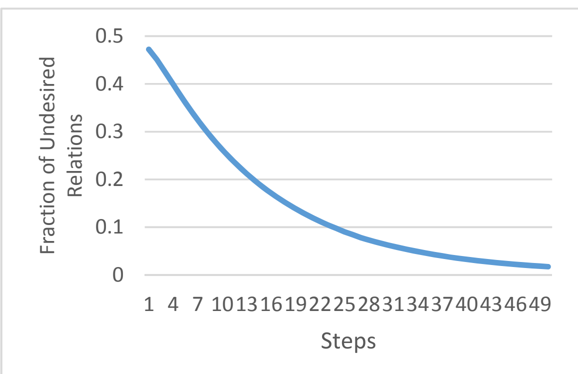
The clustering algorithm introduced in [25] is used to detect the opinion clusters. In order to evaluate the quality of these clusters, the Silhouette coefficient is calculated based on Eq. 7. Silhouette coefficient is a continuous value in [-1, 1] so that whenever this value is closer to 1 the quality of detected clusters is better.

$$S_i = \frac{b_i - a_i}{\max(b_i \; and \; a_i)} \quad (7)$$

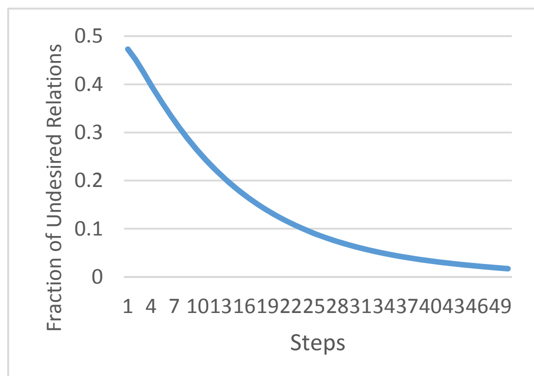
Where a_i is the average dissimilarity of i with all other data within the same cluster and b_i is the lowest average dissimilarity of i to any other cluster. Fig. 7 presents the Silhouette coefficient of opinions clusters in different steps of simulation. In this figure each step shows 100 interactions in social network. As presented this value is improved during simulation steps. Also this measure shows better quality for higher value of u.

Fig. 8 shows the results of simulation for complete graph. Fig.8(a) shows the results for $u = 0.2$. like Fig.5(a), individulas has lower chance than higher values of u for interaction. But because of more relations in comparison to scale free network, this chance is more. Each individual has many social links and consequently at first they shape several opinions clusters with few members. By continuing the simulation, this small clusters join each other and shape larger clusters. Fig.8(b) and Fig.8(c) shows the results for $u = 0.5$ and $u = 1$. In these samples like the Fig.8(a), at first there exist several small clusters. But by continuing simulation all individuals reach a consensus.

Like Fig. 6, Fig 9 presents the fraction of undesired relations in each step of simulation for complete graph. As expected these fraction is decreased over simulation steps but it dosen’t equal to 0 at the final



(a)



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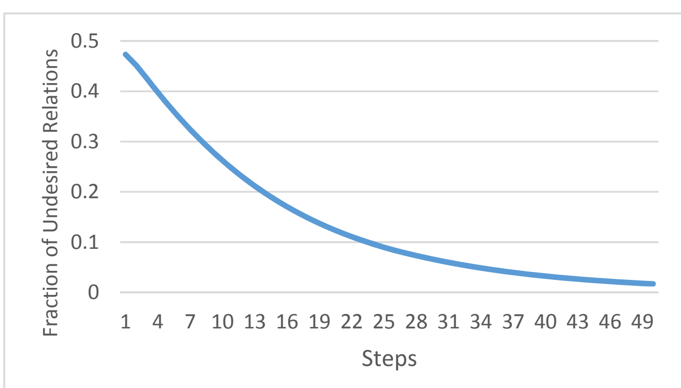
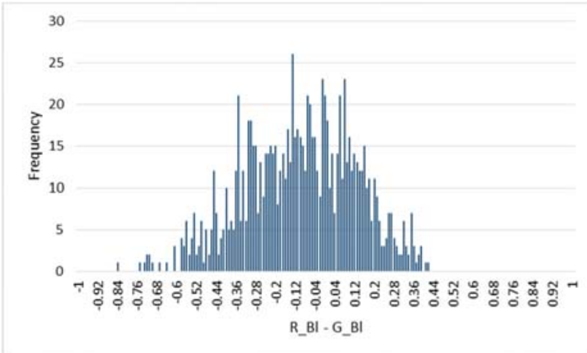
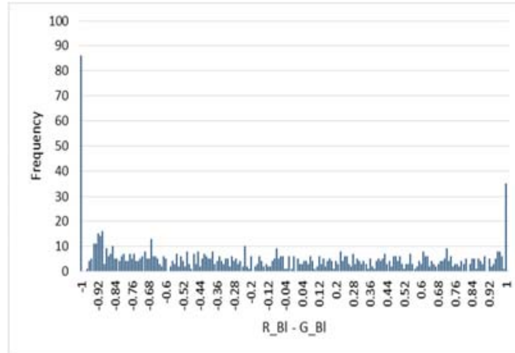


(c)

Fig. 9. The fraction of undesired relations in complete graph when (a) $u = 0.2$, (b) $u = 0.5$, (c) $u = 1$



(a)



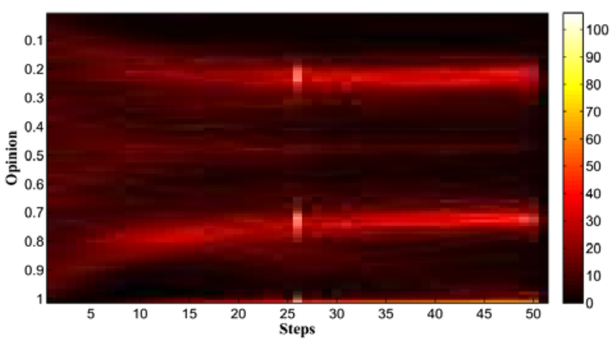
(b)

Fig. 10. The distribution of difference of receptive baseline and generative baseline at the start (a) and end (b) of simulation

step. Each step in this figure shows 1000 interactions in social network.

Fig.10 shows the number of individuals(frequency) with different values of R_Bl-G_Bl. As the receptive baseline is the fraction of out-coming positive links interpreted as tendency to be followed by others and generative baseline is the fraction of in-coming positive links interpreted as tendency to follow others, this difference can be interpreted as the tendency of opinion leadership. Fig.10(a) shows distribution of opinion leadership of individuals at the start of simulation. As shown the majority of individuals has low tendency for following or leadership. By continuing simulation the tendency of individuals to follow others or to be followed by others and the opinion leadership has been changed. Fig.10(b) shows the distribution of opinion leadership at the final step of simulation. In this step a large number of individulas are the exclusive followers while fewer ones are leaders. Others has both two tendency with different degrees.

As mentioned we try to navigate the opinion of all agents to predefined target by changing the opinion of leaders. Fig. 11 presents the result of simulations for scale free network when $TL = 0.99$ and $target = 1$. For $u = 0.5$ and $u = 1$, at first the opinions of agents converge to one value in the middle of opinion interval. By continuing the simulation opinion of agents are changed in effect of leaders and his value approaches to opinion target. For u = 0.2, the results are similar to Fig. 5. In this case the confidence interval of agents is narrow and opinion leaders have lower chance to modify the opinion of others. So leaders cannot navigate the opinion of social networks when agents



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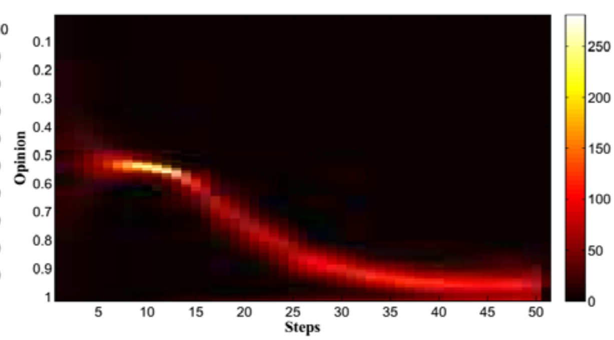

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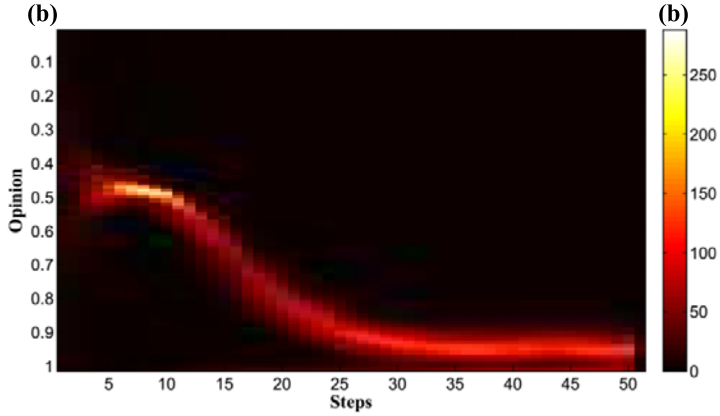

(c)

Fig. 11. The simulation results of complete graph when (a) $u = 0.2$, (b) $u = 0.5$, (c) $u = 1$

are less open minded and have a tight confidence interval.

VII. CONCLUSION

in this paper we have introduced an agent based opinion formation model considering the leadership ability of different individuals. The introduced model is based on the Deffuant model modified so that agents change their opinion according

to own and interacting neighbor leadership ability. Leadership ability is defined based on the status theory. This theory tries to detect some of the fundamental principles to indicate the link formation in signed social networks. Unlike many of other works in this area that consider a positive/ negative link as trust/ distrust and friendship/ enmity, this theory considers a link as an evaluation that one agent has about status of another agent.

The results show the individual opinions may shape some clusters or converge to a single point based on the value of confidence threshold. Because of the existence of more relations between individuals in the complete graph, individuals shape several small clusters at the first and then join these small clusters to create larger ones. Also at the first of opinion formation process the majority of society has no or low tendency to become opinion leader or follower. But by changing the type of relations they become exclusive follower, leader or intermediate leader. Also results show if the confidence interval of agents is large enough, the leaders have the ability of navigating social opinion to a predefined target.

This model can be extended by considering context in agent modeling. Context is information about the conditions that affect agent's actions. Opinion formation algorithm can be modified based on this recognized conditions. Also this model can be extended by personal features of agents like role, internal opinion, conviction power and centrality. These personal features are applicable for customization of opinion formation process for each agent. Also another point for improvement of this model is modifying the method of opinion sharing. Opinion sharing in real word has several aspects while method in this work is based on a simple shifting in opinion of agents. Improvement of this changing method for modeling complex process causes the algorithm simulate real world relations and opinion formation process more appropriately. Also the conditions in which opinion leaders can navigate the opinion of social network can be investigated.

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Sajjad Salehi is Ph.D. Candidate in Computer Engineering at Univerity of Tehran, Tehran, Iran. He has received his MSc from Department of Electrical and Computer Engineering, University of Tehran, Tehran, Iran in 2012 and his BSc in IT Engineering from University of Isfahan, Isfahan, Iran, in 2009. His research interests include Artificial Intelligence, Social Networks, Agent Based Modeling, Multi-Agent System and Data Mining.

Fattaneh Taghiyareh is a faculty member at the Information Technology Department, School of Electrical and Computer Engineering, University of Tehran since 2001. She received her Ph.D. from Tokyo Institute of Technology in 2000. Her research interests are Technology Enhanced Learning, Multi-Agent Systems, and Human-Centered Computing Systems. Her current research involves the intersection of Web-Services, Personalization, and adaptive LMSs as well as applying ontology to semantic web. She was past-manager of the Department of Information Technology at the School of Electrical Computer Engineering, and former Director of Technology Incubator, University of Tehran. She is a member of Editorial Board of International Journal of Information & Communication Technology. Currently she is supervising IT Foundation lab, e-learning lab, and multi-agent systems lab.