Opinion Formation Modeling By Agents With Internal Tendency

Sajjad Salehi
ECE Department
University of Tehran
Tehran, Iran
salehi.sajjad@ut.ac.ir

Fattaneh Taghiyareh*
ECE Department
University of Tehran
Tehran, Iran
ftaghiyar@ut.ac.ir

Received:2019/03/27 Revised:2019/06/15 Accepted:2019/07/16

Abstract- Several factors such as engagement with peer groups, government policies, personal attitudes can affect people's opinion about a specific subject. Most of scholars in this area focus on the interaction of individuals in social network and overlook other factors. In this paper, an opinion formation model is presented in which the internal tendencies of individuals are considered as an intrinsic property. In this model, people revise their opinion based on their neighbors' opinion, trust/distrust between them and their own internal tendency. By internal tendency we mean a set of internal factors which may affect the decision of individuals. Simulation results show that this model is able to predict individuals' opinion which might present their preferences to different products in social network when parameters of the model are identified and assigned. As this model can predict people's opinion in the market, it can be used in definition of a marketing or production strategy.

Keywords— Opinion Formation, Agent Based Modeling (ABM), Social Networks, Social Market, Internal Tendency

1. INTRODUCTION

Opinion formation refers to the process by which the opinion of agents about one issue has been changed over time. This evolution in opinions usually is modeled based on the interaction of agents. But different factors like governmental policies and characteristics of individuals could effect this process. Opinion may be interpreted as the preference of customer about one product and opinion formation can be considered as a tool for modeling changes in these preferences. So this model predict the future sentiment of customers about one product and market trends. These models usually represent the social network as a graph where its nodes shows the individuals and its links present the relations between individuals. Each node has some variable to describe attribute of social members while the feature of relations are presented by attributes of links. Also each node has an attribute for presenting the opinion and a method to revise its opinion over time.

Opinion of individuals usually is modeled by a numeric value. This value may have different forms including discrete [38, 39], continuous [16], fuzzy [12], probabilistic [35] or a vector [2, 30] based on the application of model. Also different internal Characteristics of individuals like internal opinion [17], the ability to satisfy other agents [8, 10, 40] and the ability to maintain own opinion [8], self-confidence [29], leadership ability [29, 31, 32] and emotion [25] can affect opinion formation process. As mentioned the relations have different attributes. A link may presents existence or lack of relations between members [16, 38], trust [12, 29] or trust/distrust [3, 4] between them. Trust/distrust usually is modeled by a signed numeric value or a tuple containing a continuous numeric value as a strength and a sign as a type of relation. Also different strategies are used to model how one individual may be influenced by others.

In this paper we introduce an opinion formation model to describe the changes in social members' preference about one product. In this model each individual has a continuous value as opinion and a couple of (strength, action) as an internal tendency. Also each individual may trust another individual, distrust him or be neutral to him. In this model agents update their opinion based on their approximation of trusted neighbors' opinion, their interacted neighbor and internal tendency. Also the trust network of individuals will be updated based on changes in their opinion.

2 . LITERATURE REVIEW

Opinion formation methods can be categorized based on the way that model the community. In these models a one or two dimensional lattice [38] or a graph [1, 20] is used for modeling social network. So each node shows one individual and features of individuals are represented by attributes of these nodes. Also links represent the relation of members that may presents the existence or nonexistence of a relation [14],trust between two individuals [17] or distrust/trust between agents [3, 4]. Although opinion formation models utilize different features for modeling each agent,all have a value to describe the opinion of them. This value might be discrete [23], continuous [16], vector of variables [2, 30] or a fuzzy number [18]. Some works consider two types of opinions; internal and external [9, 19]. In these works each individual focus on his internal opinion and try to express an external one so that it has minimum difference with his own internal opinion and external opinion of others. These works can be applicable in the cases, like negotiation, that individuals have a fixed opinion and they want to express an opinion to convince others. So individuals donâ€™t tend to change their internal opinion and only try to find a suitable external opinion. Banitch et.al [7] consider a discrete opinion and historical feedback about opinion of others and change opinion of members based on social interaction and effect of peer groups.

Many works in opinion formation literature are focused on the selection problem including product selection, election or following a leader [11, 19, 29]. Caruso and Castorina [11] try to analyze the behavior of social members in election while Ramirez and Pitt [29] investigate the impact of opinion leaders on social opinions. The opinion of individuals about products have been evaluated in [23, 30].Also the purpose of some works is designing models to direct the social opinion to predefined targets. This work try to model the dynamics of individual interaction in community. Campaign problem is considered in [19]. Finding a set of peoples whose positive opinion about an issue will maximize the overall positive opinion for the item in the community is named Campaign problem. These works could also be considered as an influence maximization problem modeled by Kempe et al. [22]. In the context of market, social opinions show the members preferences to different products [21].

As mentioned Some works in this area model the trust network between agents [17, 29]. In these works a co-evolutionary process revise agentsâ€™ opinion based on the trust network and change trust network by modifying agentsâ€™ opinion. Trust network refer to the degree of trust/distrust value between members of network. This value could be modeled explicitly [3, 4, 15] or could be derived from other features [13, 36]. These works suppose agents try to change their opinions to close it to trusted neighbors and keep it away from distrusted ones. Some works only describe the process of opinion formation [33] while others want to investigate the conditions for creating bipartite consensus in social network [3, 4]. Bipartite consensus refers to the state in which all agents have a similar opinion value divided in two category with different signs [4]. Also positive or negative relations could show the individuals evaluation from the status of others. Positive link shows higher status evaluation in mind of one individual and negative link shows he believes the other has lower status [24]. From another perspective, relations could be considered as opinion of each agent about others and these opinions could be used to predict type of new relations [15]. Vectors of opinions and similarity between them are used to calculate probability of agreement or disagreement by Sirbu et al. [36]. Chau et al. [13] modified the model introduced in [16]. They assume two agents could increase the distinction of their opinions if the difference of them is greater than predefined threshold. Deffuant [16] models the opinion with a continuous value between 0 and 1 and considers a threshold as confidence interval. If the difference of two agents' opinion is less than confidence interval, these agents could change opinion of each other.

Some works in opinion formation are intuited from physics science [6, 23, 37]. The opinion formation process can be considered as the formation of magnetic that spins turn to one direction and shape a regular formation [6]. Received feedback from society could be used to guide opinion formation process. Krause [23] uses the temperature as a feedback for controlling the process of opinion formation. This feedback might show the balance of buyers and sellers in a market. Probability of modifying the opinion of agents is affected by temperature of community. The instability of relations in a network shows the probability of changes in network. This value could be used as a feedback of social network and affect the opinion formation process [33]. Structural property of networks is mostly neglected In opinion formation models [20, 34]. Collective behavior of agents may be influenced largely by these properties so that modification of them could change the behavior of opinion formation process [5, 27]. the impact of structural position on turning some agents into leaders is investigated in [31] by considering two measurements of status theory [24]; generative and receptive baselines. Although many human behaviors are complex, these behaviors can be interpreted with simple rules. In other words human are similar to simple automata that response simple stimulus in environment [6].

3 .PROPOSED MODEL

In this section we try to present our proposed model. In this model, the opinion of each agent is a continuous value in [-1,1] presented by x_i. Also agents have an internal tendency presented by t. In this model internal tendency is represented by a couple (s, a) where s presents the strength of tendency and a shows the action that agent prefer. Strength has a continuous numeric value lied in [0, 1] while action is a discrete number with value 1, indicates tendency to buy one product, or -1, shows tendency to not buy that. The relation between agents is presented by r_{ij} that lied in [-1, 1] and i is index of first agent and j is index of second agent. When one agent, named i, trust other agent, named j, r_{ij} is greater than 0, in other hand when one agent distrust other, r_{ij} is less than 0. Also $r_{ij} = 0$ shows that agent i is neutral to agent j and agent i is not affected by this neighbor. The value of r shows the strength of relation between two agents and indicate the impact level of one agent on his neighbor. It is assumed that the network of relation between agents is static during opinion formation process. In this model each agent modify his opinion based on the opinion of his neighbors and his internal tendency. In each step first agent, named agent i, is selected randomly. Then one of the neighbors of agent i called agent j that deference of his opinion with agent i is less than d, $|x_i - x_j| < d$, is selected randomly. If there is no agent with condition $|x_i - x_j| < d$, agent i is considered as his own neighbor. d is a predefined threshold and considered as confidence interval for agents. So the opinion of agents is modified based on Equation 1.

$$x_i = OD * r_{ij} * 0.5 + ESP + (s_i - |x_i|) * max(a_i * sign(x_i),0) * |ESP - x_i| \quad (1)$$

Where OD is the difference between opinion of agent i and opinion of agent j and calculated based on Equation 2, ESP is estimated social opinion, s is the strength of internal tendency and a is its action.

$$\text{OD} = \begin{cases} x_j - x_i & if \;\; r_{ij} > 0 \\ d - |x_j - x_i| & if \;\; r_{ij} < 0 \end{cases} \quad (2)$$

As mentioned if there is no agents in neighbor of agent i that difference in their opinions is less than d, agent i is selected as his own opinion. So in this case, $(x_j - x_i)$ is equal to 0 and is ignored. ESP is the estimation of agent i from his trusted network opinion and it is calculated based on Equation 3. In proposed model, each agent know his trusted neighbors and has an opinion history of them named h. h_{ij} shows the estimate of agent i from opinion of agent j. At step 1 he suppose all his neighbors have an opinion same as his own opinion. When he interact with one of his neighbors, he update this history.

$$ESP = \frac{\sum_{j \text{ where agent i trust agent j and } |x_j - x_i| < d} r_{ij} * h_{ij}}{\sum_{j \text{ where agent i trust agent j and } |x_j - x_i| < d} r_{ij}} \quad (3)$$

So each agent change his opinion in effect of his interacted neighbor, $OD * r_{ij} * 0.5$, his estimation of trusted network opinion, ESP, and his internal tendency, $(s_i - |x_i|) * max$â€‹$(a_i * sign(x_i),0) * (ESP - x_i)$. In third case, agent notice to action derived from his opinion and action forced by internal tendency. Based on agent opinion, If his opinion is greater than 0, he prefer to select product 2 and if it less than 0 he prefer to select product 1. So when his opinion and his internal tendency has conflict, agent try to change his opinion to resolve it. It is important to note that agents consider their estimation from trusted network opinion. When their opinion is close to ESP, $|ESP - x_i|$ is small, they have less notification to their internal tendency.

4 .SIMULATION AND RESULTS

In this section, we try to explain the simulation of model and results of evaluation. In the first step we ran the simulation for a scale free network with 1000 nodes and average nodal degree of 20. in order to evaluate the model we define a measure named Deviation. In this area, agents try to form opinions similar to opinion of trusted neighbors and far from opinion of distrusted ones. So Deviation of opinion is defined as equation 4

$$Deviation = \frac{\sum_{j \text{ where agent i trust agent j and } |x_j - x_i| < d} |x_j - x_i|}{\sum_{j \text{ where agent i trust agent j and } |x_j - x_i| < d} 1} + \frac{\sum_{j \text{ where agent i distrust agent j and } |x_j - x_i| < d} d - |x_j - x_i|}{\sum_{j \text{ where agent i distrust agent j and } |x_j - x_i| < d} 1} \quad (4)$$

Figure 1 shows the value of $Deviation$ for scale free networks with different average nodal degree. Simulations ran 10 times for $d = 0.2$. vertical axis shows the Deviation while horizontal axis presents the average nodal degree. as presented, the value of $Deviation$ is decreasing while the average nodal degree of evaluated network is increasing. Since agents with more neighbors has more opportunity of interacting, they can form their opinion in effect of a larger portion of social network. So agents approach their opinion to more trusted neighbors and keep it far from more distrusted ones that cause to decrease the Deviation.

Figure 2 presents the value of $Deviation$ for network with different clustering coefficient. Clustering coefficient is a local measure that indicates the tendency of each node in a graph to form a cluster with its neighbors. As presented in Eq.5 this value is the fraction of number of triangles around one node and the potential ones. Also there is a global version of this measure to describe the overall tendency of all nodes by averaging local measurements for all nodes of graph. Figure 2 shows the value of $Deviation$ is decreased by increasing the value of clustering coefficient. For larger value of clustering coefficient agents have more dense relations with neighbors that cause they form some clusters. In other words agents form local communities where they have more local interactions and form similar opinion.

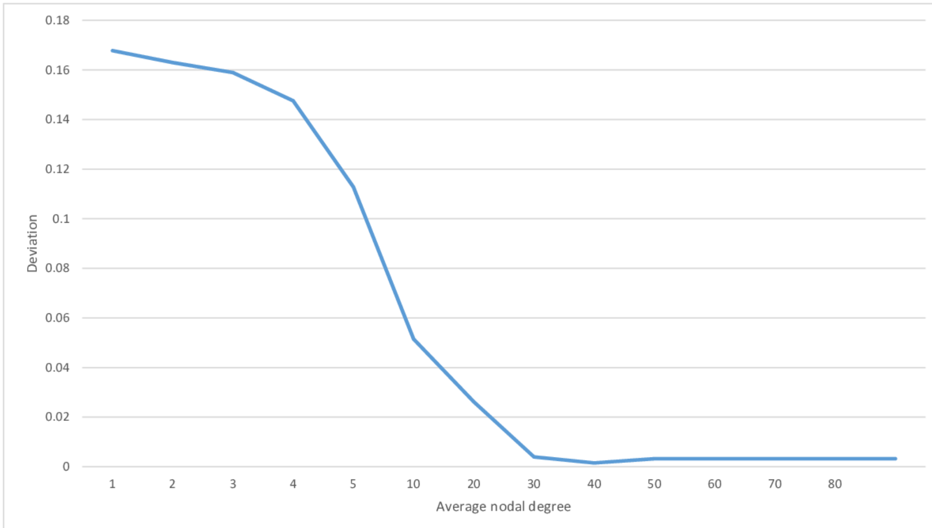


Fig1. The Deviation value for different average nodal degree

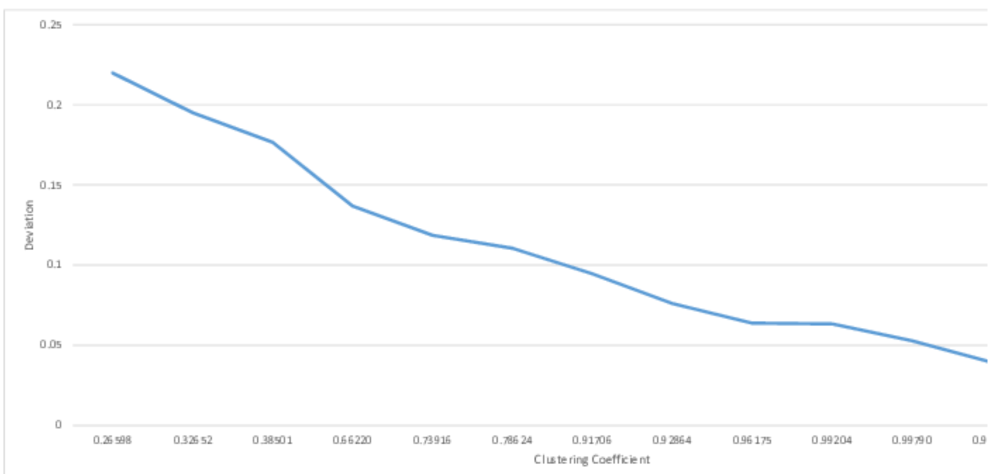


Fig 2. The Deviation value for different clustering coefficient

$$Clusterin_{Coefficient_i} = \frac{Numer\ of\ triangles\ around\ i}{\frac{k_i * (k_i - 1)}{2}}$$

$$Where\ k_i\ is\ the\ number\ of\ neighbors\ of\ node_i \tag{5}$$

In the next step we ran the simulation on Epinion dataset [41]. In this dataset individuals score products by selecting a discrete number between 1 and 5. Also each individuals may trust or distrust others. The frequency of score 1 approximately is equal zero. Therefore we assume individuals with score 2 or 3 don't recommend one product and individuals with score 4 or 5 recommend it. In other hand, by intuition from continuous opinion and discrete action [26], we assume agents with opinion less than 0.5 don't recommend one product and other agent recommend it.

TABLE 1. SIMULATION PARAMETERS

d	Strength of internal tendency	Action of internal tendency
0.2,0.5,0.8,1.0	U(0,1)	Sign(U(-1,1))
.2,0.5,0.8,1.0	$\lvert N(0,0.5) \rvert$	Sign(N(0,0.5))
.2,0.5,0.8,1.0	$\lvert N(0.5,0.5) \rvert$	Sign(N(0.5,0.5))
.2,0.5,0.8,1.0	$\lvert N(-0.5,0.5) \rvert$	Sign(N(-0.5,0.5))

We suppose agents have an opinion derived from uniform distribution at the first step. Then the simulation with different values for parameters, as presented in Table 1, ran for 380 products. Figure 3 presents the degree distribution of people in the Epinion dataset.

Then for each product, we compared actions derived from formed opinion with actions derived from distribution of opinion in original dataset and select nearest result. In other words we explored the parameter space and found best parameters for each product and then compared results of this parameters with original dataset. This comparison shows the results derived from simulation has distinction with dataset or not. For comparison the test of proportion is utilized [28]. If the result of this test is greater than or equal to 0.05, two distribution is similar. Otherwise we have two distinct distributions. Out of 380 test, only 23 test has value less than 0.05 that shows 357 derived distribution is similar to original dataset. the frequency of p-values of proportion test is presented in Figure 4.

To investigate the cause of changes in value derived from proportion test for different products, we compare this value with two features of product network, average nodal degree and clustering coefficient. Figure 5 presents the relation between average nodal degree of product network and the value derived from proportion test. This figure shows a positive correlation between these two variables. So we can conclude one of the main reasons that our model can't predict an action distribution like original distribution in dataset is the degree of nodes in social network of these products.

Also Figure 6 shows the relation of clustering coefficient and proportion test value. Like average nodal degree, clustering coefficient and proportion test has a positive correlation. In other words for networks with larger clustering coefficient, our proposed model predict more similar distribution. So average nodal degree and clustering coefficient as two structural features of product social network can affect on performance of our proposed model to predict action distribution.

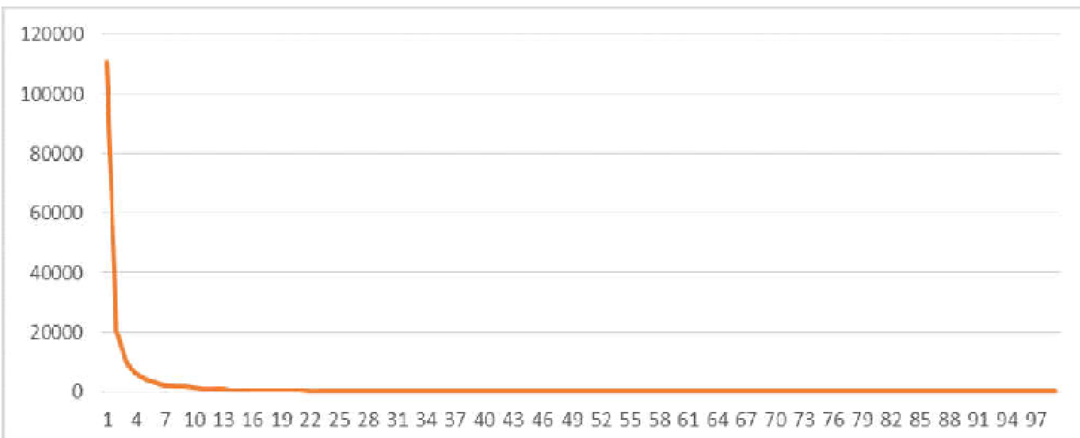


Fig 3. Nodal degree distribution in Epinion Dataset

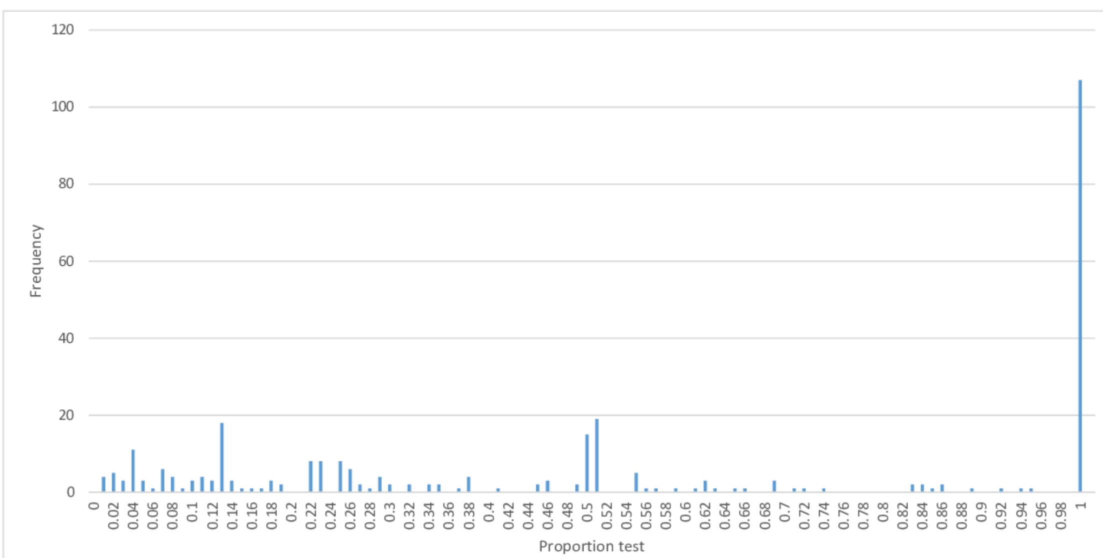


Fig 4. Histogram of proportion test value for selected products

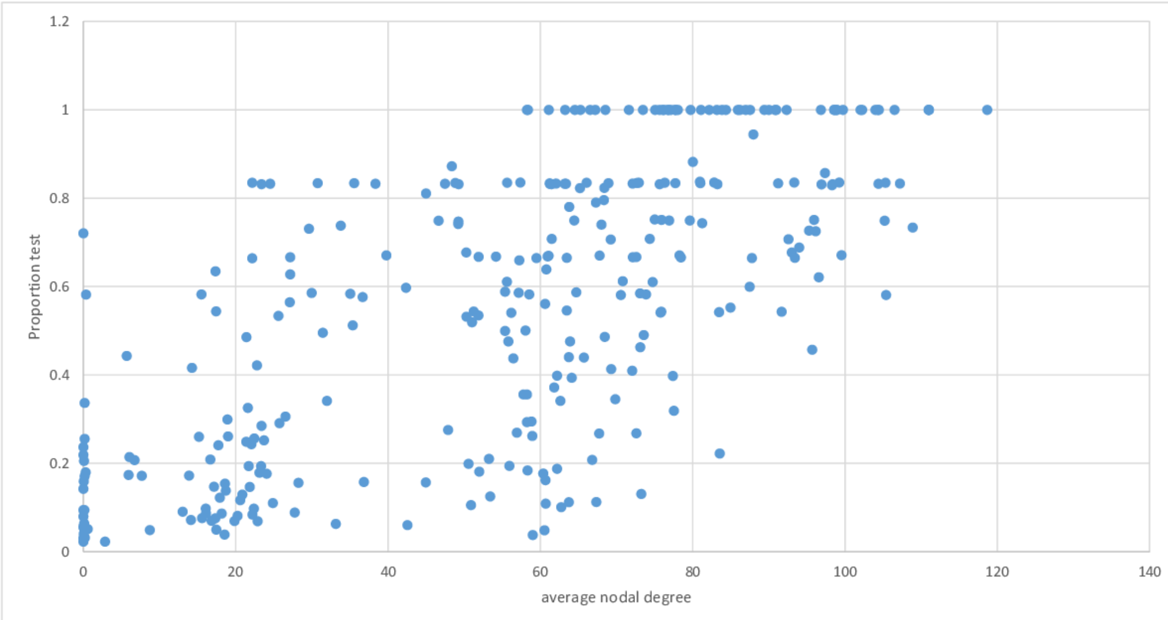


Fig 5. The relation of proportion test value and average nodal degree

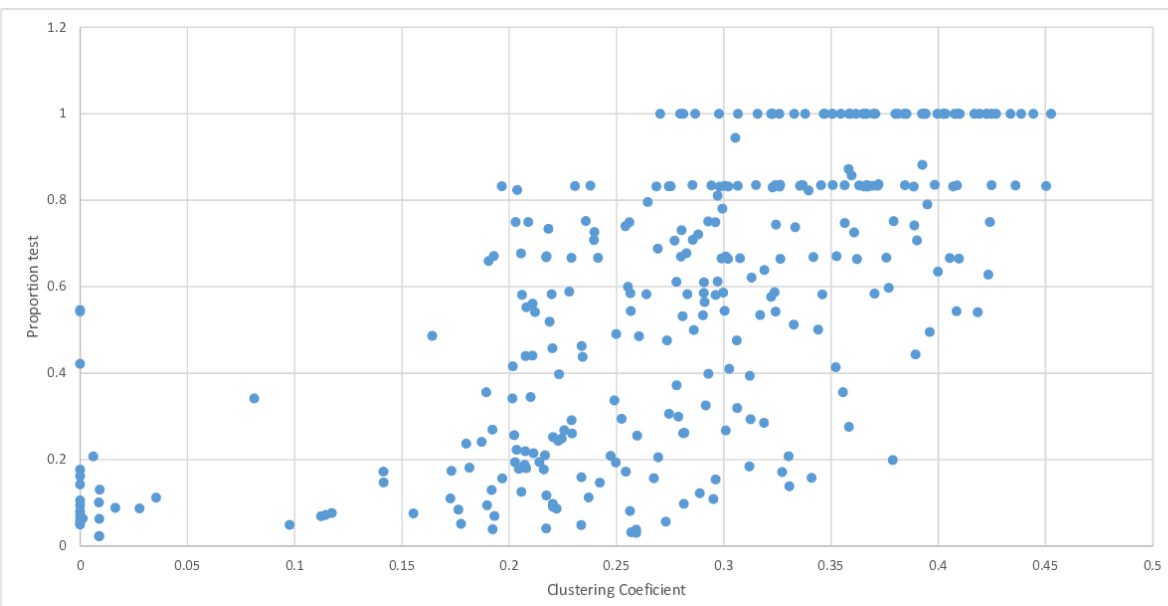


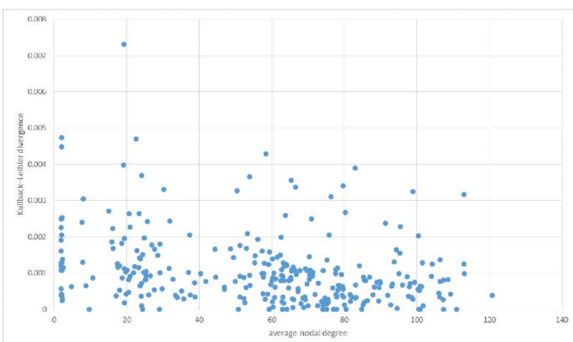
Fig 6. The relation of proportion test value and clustering coefficient

In order to investigate the effect of social network structure on the performance of the proposed model, various network characteristics were investigated. In order to compare the effect of this feature on the similarity between simulated distribution and main distribution, the Kullback-Leibler divergence criterion has been used (Eq. 6). Contrary to the proportion test, this criterion produces a measure of distances between two distributions. The number generated is between 0 and 1, and the closer to 0 the value is, the more similar two distributions are. Among the investigated cases, there is a correlation between the characteristics of clustering coefficient, the average nodal degree and the average distance between the nodes with the Kullback-Leibler divergence. The Figure 7 represents this relationship. There is a negative correlation between the two characteristics of the clustering coefficient and the average nodal degree with the Kullback-Leibler divergence, and there is a positive correlation between the average distance between nodes and the Kullback-Leibler divergence.

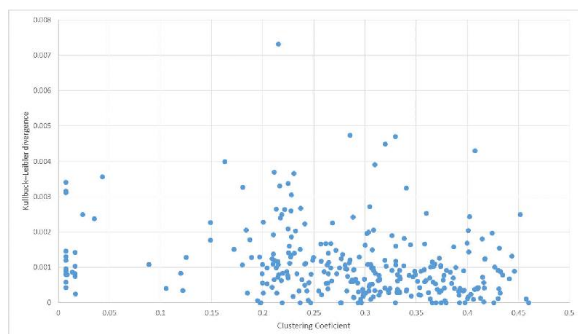
$$D_{KL} = -\sum_{x \epsilon X} P(x) log(\frac{Q(x)}{P(x)}) \quad (6)$$

As mentioned, we suppose the internal tendency of agents can be derived from some distributions and we evaluate our model by creating these value based on distributions explained in Table 1. Now we try to predict the internal tendency of each agent to one product from his internal tendency to other products. In the first step, for each product, its frequent pattern is extracted based on the common individuals. In other words, for each product, all individuals that score that is considered. Then other products that more than 20% of these individuals expressed his opinion about them are selected as frequent pattern. In the second step for each product one decision tree is created based on his frequent pattern and entropy measurement. in the second step for each individual the value of internal tendency is approximated based on his opinion about other products and distribution of opinion on decision tree. Figure 8 presents the distribution of proportion. test for simulation of model by extracting internal tendency from decision tree. Out of 297 selected products, only 20 test has value less than 0.05 that shows 277 derived distribution is similar to original dataset. In addition to average nodal degree and clustering coefficient that have effect on opinion prediction, we consider the fraction of average distance of selected agents to create frequent pattern and average distance of all individuals.

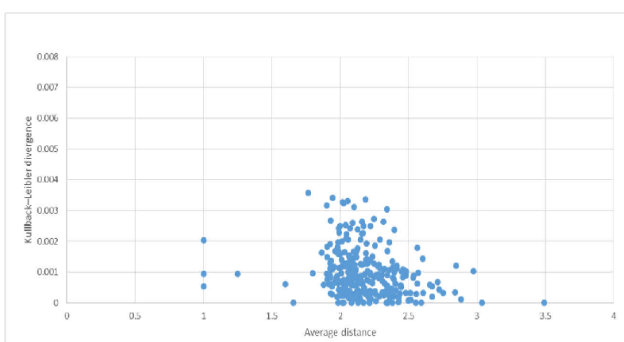
Figure 9 shows this fraction has an positive correlation with proportion test value. So for larger fraction, we can assume that selected individuals are the representative of larger range of social network and the approximated internal tendency is more exact. Therefore the action distribution is more similar to original one. Figure 10 shows the Correlation between the dispersion of the selected nodes with the Kulbock-Leibler divergence criterion. The horizontal axis represents the ratio of the average distance between nodes in the selected graph to the average distance of nodes in the main graph. The more distant selected nodes are, the larger the ratio is. The ratio indicates that the selected nodes are extracted from a community or are representative of whole society. As shown in the



(a)



(b)



(c)

Fig 7. The relation of Kullback-Leibler divergence value and (a) Average Nodal Degree, (b) Clustering Coefficient, (c) Average Distance

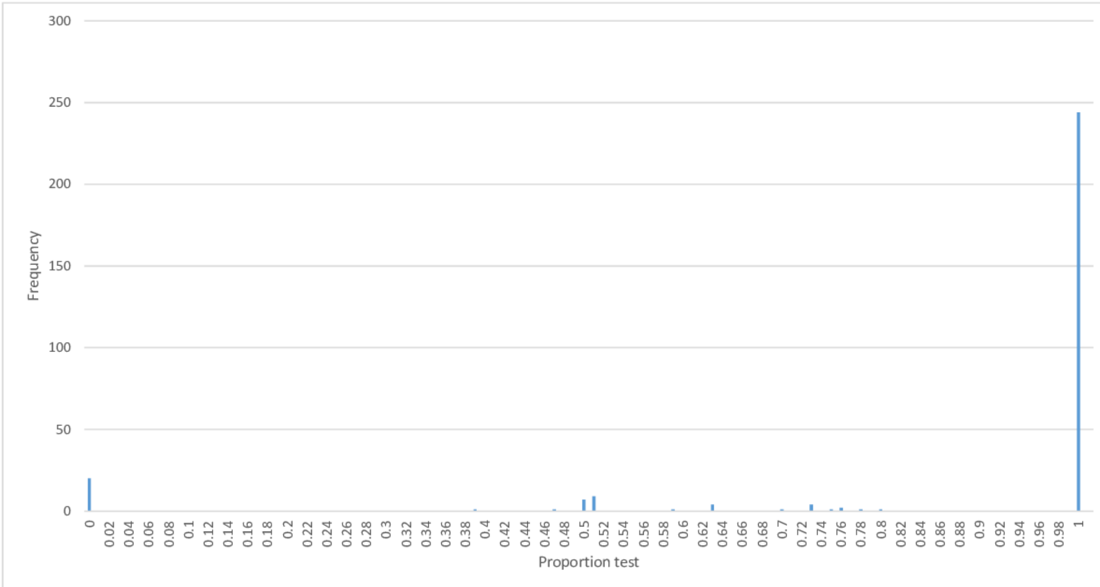


Fig 8. Histogram of proportion test value for case where internal tendency is approximated based on decision tree

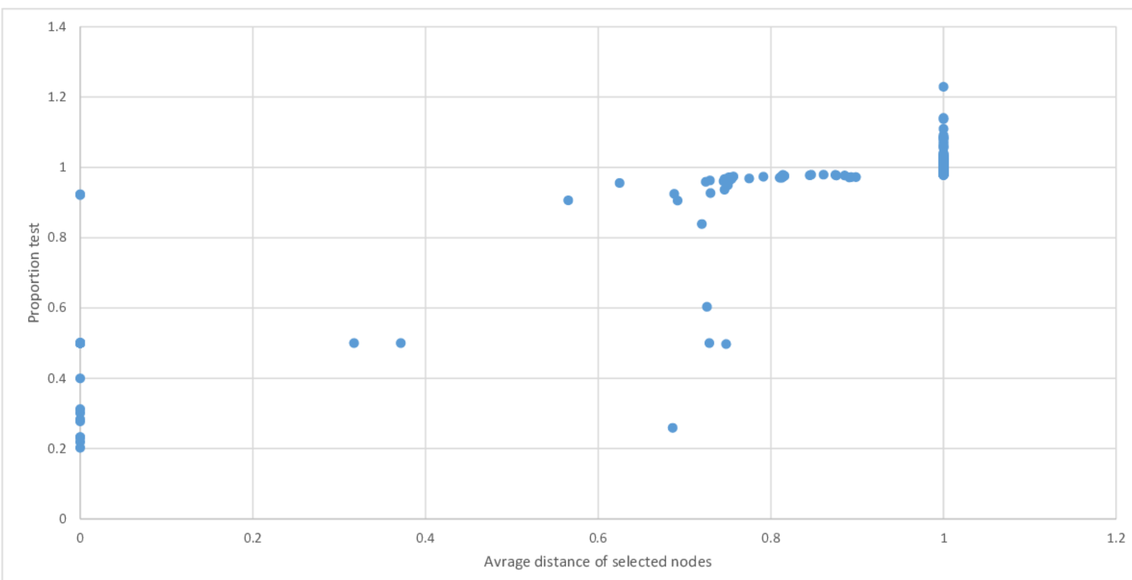


Fig 9. The relation of proportion test value and fraction of average distance of selected individuals based on frequent patterns and all individuals

figure, these two variables are negatively correlated with each other. Therefore, it can be concluded that selecting more diverse and wider individuals from the society can lead to a better result from the model.

5 .CONCLUSION

In this paper, we have introduced a model for opinion formation in social network where agents notice their internal tendency in addition to their social relations. In this model opinion of each agent has modeled by a numeric value that presents preference of one agent about one product. Also internal tendency is modeled by two value of strength and action. In each interaction one agent modify its opinions based on the interaction with one of its neighbors, his approximation from social opinion and internal tendency. In order to represent the the social network, a directed signed graph has been used. In this network each agent is modeled by one node and trust relation is modeled by signed weighted arcs. The proposed model can be used to predict opinion of social network about one product. For this, the structure of relations in social network must be identified. Also a buying history of individuals and opinion of some individuals in social network

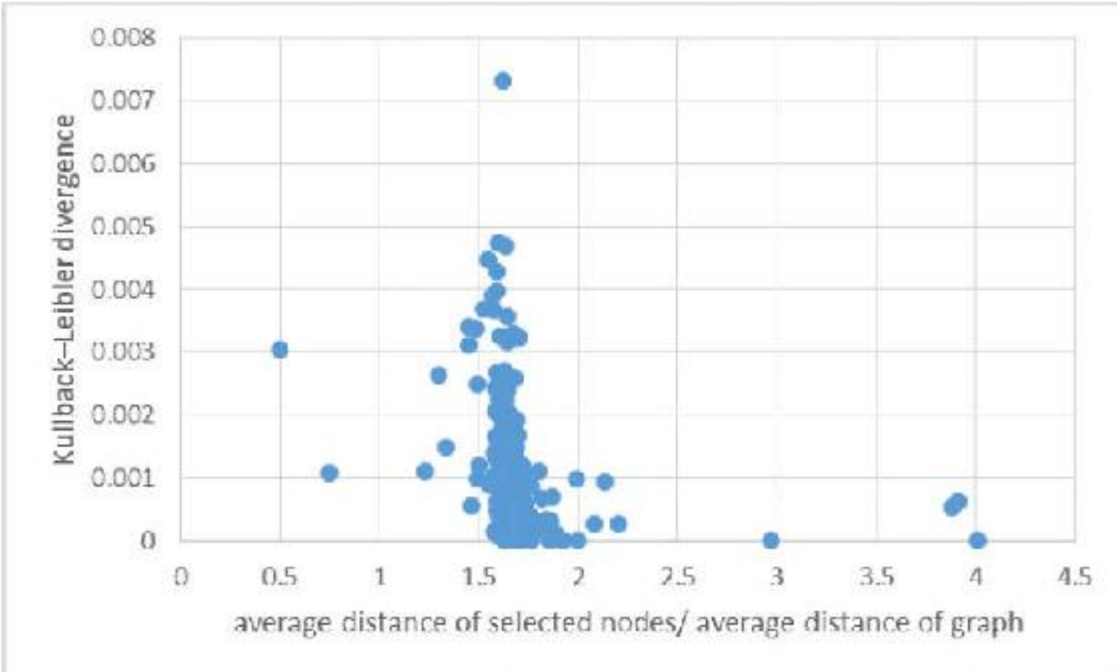


Fig 10. The relation of Kullback-Leibler divergence value and dispersion of the selected nodes

about that product is needed. So we can ran model for all individuals and detect the distribution of opinion in social network.

Considering the personal features of agents like age, race, leadership ability, selfishness and ... can be improve the results of opinion formation process. Also this model can be extended by using structural features of social network like changes in relations and pattern of them. In this area other structural theory like structural balance and status theory has valuable information.

REFERENCES

[1] M. Afshar and M. Asadpour, Opinion formation by informed agents. *Journal of Artificial Societies and Social Simulation*, vol. 13, no. 4, p. 5, 2010.

[2] A. Alaali, B. T. R. Savarimuthu, et al. Vector opinion dynamics: An extended model for consensus in social networks. In *2008 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, 2008, IEEE Computer Society. vol. 3, pp. 394–397.

[3] C. Altafini and Gabriele Lini, "Predictable dynamics of opinion forming for networks with antagonistic interactions", *IEEE Transactions on Automatic Control*, vol. 60, no. 2, pp. 342–357, 2015.

[4] C. Altafini, "Consensus problems on networks with antagonistic interaction", *IEEE Transactions on Automatic Control*, vol. 58, no. 4, pp. 935–946, 2013.

[5] F. Amblard and G. Deffuant, "The role of network topology on extremism propagation with the relative agreement opinion dynamics", *Physica A: Statistical Mechanics and its Applications*, vol. 343, pp. 725–738, 2004.

[6] P. Ball, "The physical modelling of human social systems", *Complexus*, vol. 1, no. 4, pp. 190–206, 2003.

[7] S. Banisch and E. Olbrich, "Opinion polarization by learning from social feedback", *arXiv preprint arXiv:1704.02890*, 2017.

[8] K. Bhawalkar, S. Gollapudi and K. Munagala, "Coevolutionary opinion formation games", In *Proceedings of the forty-fifth annual ACM symposium on Theory of computing*, 2013, ACM. pp. 41–50

[9] D. Bindel, J. Kleinberg and S. Oren, "How bad is forming your own opinion?", *Games and Economic Behavior*, vol. 92, pp. 248–265, 2015.

[10] S. Biswas, A. Chatterjee and P. Sen, "Disorder induced phase transition in kinetic models of opinion dynamics", *Physica A: Statistical Mechanics and its Applications*, vol. 391, no. 11, pp. 3257–3265, 2012.

[11] F.Caruso and P. Castorina, "Opinion dynamics and decision of vote in bipolar political systems", *International Journal of Modern Physics C*, vol. 16,

no. 09, pp. 1473–1487, 2005.
[12] S. Chatterjee and E. Seneta, "Towards consensus: some convergence theorems on repeated averaging", *Journal of Applied Probability*, vol. 14, no. 1, pp. 89–97, 1977.
[13] H. F Chau, C. Y Wong, F. K Chow and C. -H. F. Fung, "Social judgment theory based model on opinion formation, polarization and evolution", *Physica A: Statistical Mechanics and its Applications*, vol. 415, pp. 133–140, 2014.
[14] G. Deffuant, F. Amblard and G. Weisbuch. "Modelling group opinion shift to extreme: the smooth bounded confidence model", *arXiv preprint cond-mat/0410199*, 2004.
[15] G. Deffuant, T. Carletti and S. Huet, "The leviathan model: Absolute dominance, generalised distrust, small worlds and other patterns emerging from combining vanity with opinion propagation", *arXiv preprint arXiv:1203.3065*, 2012.
[16] G. Deffuant, D. Neau, F. Amblard and G. Weisbuch, "Mixing beliefs among interacting agents", *Advances in Complex Systems*, vol. 3, no. 01n04, pp. 87–98, 2000.
[17] M.Förster, A. Mauleon and V. J Vannetelbosch, "Trust and manipulation in social networks", *Network Science*, vol. 4, no. 02, pp. 216–243, 2016.
[18] A. Gasparri and G. Oliva, "Fuzzy opinion dynamics", In *2012 American Control Conference (ACC)*, IEEE, 2012. pp. 5640–5645.
[19] A. Gionis, E. Terzi and P. Tsaparas, "Opinion maximization in social networks", In SIAM International Conference on Data Mining (SDM), pp. 387–395, 2013.
[20] M. Jalil, "Social power and opinion formation in complex networks", *Physica A: Statistical Mechanics and its Applications*, vol. 392, no. 4, pp. 959–966, 2013.
[21] H. C Kelman, "Processes of opinion change", *Public opinion quarterly*, vol. 25, no. 1, pp. 57–78, 1961.
[22] D. Kempe, J. Kleinberg and É. Tardos, "Maximizing the spread of influence through a social network", In *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*, ACM, 2003. pp. 137–146.
[23] S. M. Krause and S. Bornholdt, "Opinion formation model for markets with a social temperature and fear", *Physical Review E*, vol. 86, no. 5, p. 056106, 2012.
[24] J. Leskovec, D. Huttenlocher and J. Kleinberg, "Predicting positive and negative links in online social networks", In *Proceedings of the 19th international conference on World wide web*, ACM, 2010. pp. 641–650.
[25] A. Mansouri and F. Taghiyareh, "Toward an emotional opinion formation model through agent-based modeling", In *2017 7th International Conference on Computer and Knowledge Engineering (ICCKE)*, IEEE, 2017. pp. 14–19.
[26] André CR Martins, "Continuous opinions and discrete actions in opinion dynamics problems", *International Journal of Modern Physics C*, vol. 19, no. 04, pp. 617–624, 2008.
[27] C. Nardini, B. Kozma and A. Barrat, "Who's talking first? Consensus or lack thereof in coevolving opinion formation models", *Physical Review Letters*, vol. 100, no. 15, pp. 158701, 2008.
[28] R. Lyman Ott and Micheal T. Longnecker, *An introduction to statistical methods and data analysis*. Nelson Education, 2015.
[29] D. Ramirez-Cano and J. Pitt, "Follow the leader: Profiling agents in an opinion formation model of dynamic confidence and individual mind-sets", In *2006 IEEE/WIC/ACM International Conference on Intelligent Agent Technology*, IEEE, 2006. pp. 660–667.
[30] S. Salehi and F. Taghiyareh, "Decision making improvement in social marketing strategy through dependent multi-dimensional opinion formation", In *Computer and Knowledge Engineering (ICCKE), 2014 4th International eConference on*, IEEE, 2014. pp. 111–116.
[31] S. Salehi and F. Taghiyareh, "An agent based positional model for opinion formation in social networks", In *The Eighth International Symposium on Telecommunications (IST 2016)*. IEEE, 2016.
[32] S. Salehi and F. Taghiyareh, "The impact of structural position on opinion leadership in social network", *International Journal of Information and Communication Technology Research*, vol. 8, no. 4, pp. 45–54, 2016.
[33] S. Salehi and F. Taghiyareh, "Introducing a more realistic model for opinion formation considering instability in social structure", *International Journal of Modern Physics C*, vol. 27, no. 11, pp. 1650136, 2016.
[34] S. Salehi and F. Taghiyareh, "A bottom-up algorithm to create structurally balanced social networks by modifying the sources of tension". In *accepted at Third International Conference on Web Research (ICWR 2017)*. IEEE, 2017.
[35] F. Schweitzer and J. A. Hołyst, "Modelling collective opinion formation by means of active brownian particles", *The European Physical Journal B-Condensed Matter and Complex Systems*, vol. 15, no. 4, pp. 723–732, 2000.
[36] A. Sîrbu , V. Loreto, Vito D. P Servedio and F. Tria, "Opinion dynamics with disagreement and modulated information", *Journal of Statistical Physics*, vol. 151, no. 1-2), pp. 218–237, 2013.
[37] P. Sobkowicz, "Modelling opinion formation with

physics tools: Call for closer link with reality", *Journal of Artificial Societies and Social Simulation*, vol. 12, no. 1, p. 11, 2009.
[38] K. Sznajd-Weron and J. Sznajd, "Opinion evolution in closed community", *International Journal of Modern Physics C*, vol. 11, no. 06, pp. 1157–1165, 2000.
[39] S. Tanabe and N. Masuda, "Complex dynamics of a nonlinear voter model with contrarian agents", *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 23, no. 4, p. 043136, 2013.
[40] Allan R Vieira, Celia Anteneodo and Nuno Crokidakis, "Consequences of nonconformist behaviors in a continuous opinion model", *Journal of Statistical Mechanics: Theory and Experiment*, 2016, no. 2, p. 023204, 2016.
[41] Epinions social network. https://snap.stanford.edu/data/soc-Epinions1.html. Accessed: 2018-04-14.

Sajjad Salehi has received his Ph.D. from Department of Electrical and Computer Engineering, University of Tehran, Tehran, Iran in 2019. His research interests include Artificial Intelligence, Social Networks Analysis, Agent Based Modeling, Multi-Agent System and Data Mining

Fattaneh Taghiyareh is associate Professor of Computer Engineering- Software and Information Technology, at the University of Tehran, where she has served since 2001. She received a Ph.D. in Computer Engineering- Parallel Algorithm Processing from the Tokyo Institute of Technology in 2000. Her current research involves “opinion Formation in Social networks”, “Semantic Web”, “Social learning”, “Agent based Modeling”. She is a member of Editorial Board of International Journal of Information & Communication Technology Research.