JEL Classification: D83, D85, D91 https://doi.org/10.35945/gb.2019.08.021

THE EFFECT OF NETWORK TYPES ON HERD BEHAVIOR

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KEYWORDS: NETWORK ECONOMICS, HERDING BEHAVIOR, BEHAVIORAL ECONOMICS.

For citation: Bichia, Q. (2019). The Effect of Network Types on Herd behavior, *Globalization And Business, №8*, pp. 161-169. https://doi.org/10.35945/gb.2019.08.021

INTRODUCTION

Humans are social beings and opinions of people around them has a significant impact on their decisions. Often, under scarcity of information, people observe the behavior of others and imitate them, that is, they resort to group behavior. Existing literature on the influence of a group suggests that a small number of individuals do indeed influence decisions of majority. This is evident from the process of spread of new technologies in agriculture, improved seeds and pesticides, dissemination of innovations, patterns of digital markets and spread of using new medicines among doctors.

Mathematical models of graph theory are used for the analysis of economic or other relations. The use of graphs to study economic problems is a fairly new, albeit rapidly growing direction in research. A particular network of connections is represented by nodes (individuals) and edges (connections). For example, below is a graph that represents a network of peers' connections at the university. These 10 nodes correspond to 10 students, and the 14 edges are for friendships between them. According to this network, student 1 befriends 2 and 4, while student 3 befriends 2, 5, 6 and 9. It is possible to analyze public opinion formation, social training, investor behavior and many other interesting issues with similar graphs.

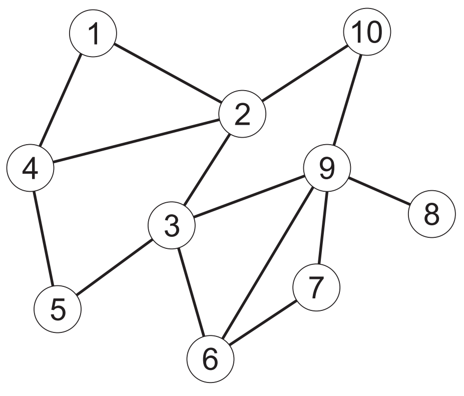


Figure 1. Network of friendly links between university peers.

The influence of opinion leaders is especially important in the Internet age, when the dissemination of ideas is quite easy and accelerated. Social influencers, who are thought leaders, make up a small part of a society. To analyze their impact D. Watts and P. Dodds considered a model of public opinion formation with influencers as 10% of the total population (Watts & Dodds, 2007). As a result, they conclude that socially influential individuals are more difficult to find than the average person and it may even be more difficult to mobilize them. Another example where thought leaders can play an important role is the early adopters of any innovation or trend. Influential people can lead group behavior and disseminate some news to the public at large.

This indicates that networking between people is very important in defining the role of thought leaders. If the average number of individual connections is low, people can more easily be influenced and the role of opinion leaders is immense. Conversely, if the average number of individuals with connections is high, only individuals with lower than average connections may be influenced by opinion leaders (ibid). A network of connections is a group of individuals, families, friends, supporters, or those who have some form of communication with an individual within a certain social system (Valente, 1996).

It is noteworthy that some scholars argue that large-scale changes in public opinion do not come from individuals with strong influence. These changes are largely caused by individuals who are easily influenced by others and themselves easily influence other individuals. The era of the Internet has brought society closer together, making it easier for one part of it to influence other members. Yet paradoxically, society seems more fragmented than ever. The level of influence of opinion leaders through the Internet has increased significantly. That is why it is justified to analyze hyperinfluential individuals, who influence very large groups of people (Watts & Dodds, 2007). It is unexpected that hyperinfluential people on average are less likely to induce group behavior than those with weaker influence and even average influence. It seems that existence of early adopters at high variation in interpersonal relationships reduce the chance of emergence of group behavior.

Observations on random networks allows for some interesting conclusions. However, people often do not associate with others on the basis of randomness. Usually, when establishing relationships, people consider certain indicators such as social role (Merton, 1957), group attribution (Feld 1981), homogeneity (McPherson et al., 2001) and others. All of this creates different internal structures in the network of connections. Consequently, each requires a different analysis.

An important feature of a network is its density, which indicates the share of connections actually existing between potential connections that could exist and is highest when all possible connections are actually realized. The density of the connection network varies from 0 to 1 and is maximal when we have a full network (all individuals are connected to all others). In low-density conditions, the number of connections is lower and information is disseminated more slowly among individuals (Jackson, 2011, pp. 511–585).

There are several empirical and experimental studies that indicate that people use the threshold rules in social conditions. The threshold rule implies that there is a certain critical value (threshold) whereby people change behavior and below it they respond differently. H. Young showed (Young, 2006) that the massive shift to hybrid maize seeds by American farmers in the 1940s could only be explained by the threshold rule. In the laboratory experiment, where participants had to identify the majority of the 24-person group, they found that people used the threshold rule at a critical rate of ½ (Latané and L'Herrou, 1996). Research has shown that computer simulations across different networks give realistic results and with repeated interactions of individuals three fundamental phenomena emerge in networks: consolidation, grouping, and sustained diversity. The consolidation refers to formation of the common choice among members, the grouping of the members means that individuals in the neighborhood of the network grow similar, resulting in a more homogeneous groups, and sustained diversity is kept by minority with the ability to keep different characteristics despite the influence from others.

Imitation between firms leads to emergence of leaders. The bigger, more successful and prestigious a firm is, the more informed other firms think it is and they tend to repeat its behavior. The emergence of followers also depends on the level and number of links the leader has with other firms (Haveman, 1993). Having a central position in the network is important because closely connected firms are better informed.

Imitative behavior may also be the cause of the "clustering" of foreign direct investments. A leader entering a foreign market may be followed by followers who repeat the same behavior, ensuring that an approximate balance of competitive opportunities is maintained and that the followers do not lose competitiveness with the leader. Imitation is also observed when there is competition between firms in research and development. The first inventor of new technology can patent his invention, so one firm's rise in research and development costs is followed by competitors' similar behavior, which results in excessive investment in a particular industry (Lieberman and Asaba, 2006).

Updating information in an incomplete network is particularly difficult, as agents are unaware of what information others possess and need to make a guess instead. A mathematical model of the network is useful for dealing with different types of examples, such as analyzing civil unrest and protests. Short distance connections can be caused by the geographical characteristics of social dissatisfaction, and long distance connections can be explained by many different factors (Braha, 2012). Especially interesting are the scale-free networks, in which degree (the number of connections with neighboring members) is exponentially distributed, indicating the existence of closely related individuals - hubs. This happens in networks that are constantly growing with the addition of new members, and new members are more inclined to associate with individuals who are already connected to many other individuals. Analyzing networks with such distributions helps to explain the phenomenon of diffusion and epidemic spread.

The analysis of large networks is associated with great difficulty, which is why it is more appropriate to observe particular cases. One example of such an analysis is that 10% of the total population can change the behavior of the rest of the population if they never change their own opinion and stay firmly on it (Xie et al., 2011). The authors came to this conclusion by analyzing the complete graphs of a network (all individuals in the complete graph are related to all others). They also concluded by simulating a scale-free network of Erdős–Rényi random graphs that the degree of the system is the same as that of complete graphs but with a lower average number of connections, the consensus time drops slightly faster. It is interesting to see whether similar results can be drawn from the analysis of individuals who are motivated by the utility level.

HERD BEHAVIOR UNDER DIFFERENT NETWORK SYSTEMS

Networks greatly influence various processes and their dissemination. For example, dissemination of innovation depends not only on how valuable the technology is to people, but also on what channels will be used to spread it and who will spread the information. In order to draw conclusions, it is advisable to compare different types of networks in terms of the prevalence of group behavior within them. In this regard, the present study deals with four types of networks: small world, one-hub (one central figure), multi-hub (many central figures) and two-component (two closely related groups with weak links between groups).

Computer simulations of group behavior formation allow for analysis of general patterns. The small-world random network is a simple base, the extension of which allows for deeper observations. Such a network could be a network of friends on Facebook, a network of college students or many others. They are characterized by a large component and short distances between any two individuals in the network

(Jackson, 2019, p. 50). Small-world random networks can be extended by introducing a closely related element into the network. The simplest network with closely related node is star network. In such a network, all individuals are connected through one central figure, and there are no direct connections. The central figure, the so-called hub, plays a key role in disseminating information within the network. Internet networks, connected though servers are such networks.

A multi-hubbed unevenly connected network well describes the characteristic of individuals that they often resort to preferential attachment - individuals (or organizations) that are more connected are more desirable than others. This feature is widespread among individuals and many situations are characterized by it (frequency of word use, distribution of city sizes, distribution of wealth, number of citations in scientific articles...). This means that nodes with multiple edges are more likely to acquire new ones, while less connected ones have less chance of making new connections. Such a relationship is often described by power law and is known as Zipp's law (Jackson, 2011, pp. 525). Such relationship leads to the emergence of certain hubs or central figures that spread information to many individuals and may be thought as leaders or experts in a particular situation. In addition to favorable connectivity, such networks are characterized by freedom from scale effects, which is particularly useful for analyzing such networks. As for a two-component network, such a network is useful for analyzing a somewhat polarized society. In the case of the behavior of loyal customer groups on both sides of the duopoly market or the formation of two major political or other opinions, public behavior can be described in terms of such a network.

Within this study, a random (small-world type), single-hub, multi-hub and two-component network of 150 individuals was selected for analysis.

We have to define some variables to formalize the model. The paper follows Jackson's notation (Jackson, 2011, pp. 511–585). The network can be represented as a graph of N nodes with a finite number of members n. The graph, i.e., the network, is (N, g) pair where g is the nXn proximity matrix. g_{ij} represents the relationship between i and j. Relationship can be of many kinds, but only $g_{ij} \in \{0,1\}$ type of relationships are considered within this work.A relationship between to individuals either exists ($g_{ij} = 1$) or not ($g_{ij} = 0$). Assume that $g_{ii} = 0$ meaning that individuals don't have relationships with themselves. If i and j nodes are connected, their relationship belong to the graph $ij \in g$ and ij is called an edge or a connection.Sub-network(N', g') is called a component if N'⊂N, g'⊂g and there is a path from any node $i \in \mathrm{N}'$ to any node $j \in \mathrm{N}'$ in g'. Moreover, no node $l \in \mathrm{N}$ that is not a part of the component $l \notin \mathrm{N}'$, has any connection to nodes within the component.In this regard, the two-component network mentioned above does not strictly follow the definition. It is more freely defined as there are couple of connections between two mostly separated components.

The neighbourhood of node i is given by $\mathrm{N}_i(g) = \{j | ij \in g\}$, which is the set of all nodes that are connected to i. The degree of a node in a network is equal to the number of his neighbours $\mathrm{d}_i(g) = |\mathrm{N}_i(g)|$. The average degree in a network is given by $\frac{\sum_i \mathrm{d}_i(g)}{n}$. The probability of forming a link with existing nodes in a network under preferential attachment is

$$P_i = \frac{\mathrm{d}_i(g)}{\sum_j \mathrm{d}_j(g)}$$

Unlike random networks, where every node has an equal chance of forming a link.

The density of a network is given by

$$D(g) = \frac{\sum_j \mathrm{d}_j(g)}{n(n-1)}$$

Some individuals are more central than others under preferential attachment and this type of random networks describe social connections better than other networks. Betweenness centrality describes how particular node plays a central role in the dissemination of information to other members of the network, or how important it is as a mediator among others:

$$C_B(l) = \frac{1}{n_B} \sum_{i,j \in N} \frac{\sigma_{i,j}(l)}{\sigma_{i,j}}$$

Where $\sigma_{i,j}$ is the number of shortest paths between i and j, while $\sigma_{i,j}(l)$ is the number of shortest paths between i and j that pass through l. n_B is the normalization coefficient and $n_B = (n-1)(n-2)$, where $l \neq i \neq j$. If one of them is equal to l then $n_B = (n-1)n$ (Mazalov and Chirkova, 2019, pp. 117-120).

The existence of networks with one or more central members in social relations is natural and there are numerous examples of such distributions. For example, the co-authoring network of mathematical scientific publications, which comprises 10 747 articles. There are 4 local stars in this network that are most closely associated with other mathematicians. Consequently, their centrality rates are also highest (ibid., pp. 155-161).

SIMULATION RESULTS IN DIFFERENT NETWORKS

The present study deals with the dissemination of a particular product, innovation, opinion, norm, or a belief in small-world, single-hub, multi-hub, and two-component networks, and the analytical implications of disseminating the two opposing opinions through group behavior. The characteristics obtained by observing the simulations are summarized and the findings are presented. Thus, the study consists of two parts: simulations of the dissemination of one opinion and simulations of the dissemination of two opposing opinions in the network. In the case of a single opinion, simulations were performed from a randomly selected member, the most connected and the least connected member. Connection density on the one hand is given by the quality of the agent in the network and on the other hand by its intermediate centrality. It was a matter of interest as to when a particular product or idea would reach full distribution in the network.

The process of spreading group behavior is as follows: Every individual receives some signal s_i about a binary decision. Action set is given by $\{a, b\}$. Individuals make the first decision based on their signals because they have no other information. According to the prior belief, both alternatives can be optimal with equal probabilities. In the next step, every individual looks at the decisions of those in his or her neighborhood and updates his or her belief by the Bayes rule - $\Pr\left(\omega = 1 \middle| s_i, H_t, \mathrm{N}_i(g)\right) = \frac{\Pr\left(s_i=1 \middle| \omega=1, \mathrm{N}_i(g)\right) \cdot \Pr(\omega=1)}{\Pr(s_i=1)}$, where $\omega\epsilon\{0,1\}$ is an even that an optimal choice is a (when $\omega = 0$) or b (when $\omega = 1$). $H_t$is history of strategies chosen by individuals in the past and $\mathrm{N}_i(g)$ is the neighbourhood of i within the network g. If the optimal action is changed after belief updating (if the probability exceeds 0.5), individuals will switch their choice. Otherwise they will keep their old action. On the next step they observe others' actions again and decide whether to change own action or not and so on. After some stages, a stable point is reached where no one is willing to change his decision after observing the choice of neighbors in the network. The study compares the times needed to reach stability in different types of networks.

A. DIFFUSION OF AN OPINION WITHIN A NETWORK

Simulations have shown that the speed of propagation of a belief varies according to who is the source of this process. However, the difference is not big within a small world network. As it turns out, full distribution occurs in at least 4 and a maximum of 20 periods, and the average time of full distribution varies from 6.5 to 8.6, depending on whether the most connected member is the source or the least connected one. In the non-random propagation simulations, the members were selected based on the number of their connections, i.e. the highest and the lowest degree according to $\mathrm{d}_i(g)$. On the other hand, considering the betweenness centrality of $C_B(l)$ calculated for each member, the individuals with the highest and lowest values were chosen.

The result is quite different if there is one central figure. In this case, the full spread occurs at a minimum of 10 and a maximum of 206 periods and the average time of full spread varies from 20.5 to 36. This means that the presence of one central figure prevents information from spreading across the network, as there is preferential attachment and some members can only acquire one connection. If there are several central figures, the full spread occurs in at least 3 and a maximum of 122 periods and the average time of full spread varies from 3.9 to 14.9. In a two-component network, full adoption occurs quite rapidly - at least 5 and up to 36 periods, and the average time of full adoption varies from 9 to 13.3. Although the connection between components is almost non-existent, a small number of existing links play a critical role in rapidly disseminating a behavior.

B. CONFRONTATION OF TWO OPPOSING OPINIONS WITHIN A NETWORK

It is interesting to see how often one view overcomes another or whether their stable coexistence is possible when two opposing opinions are being spread in a network. It can be observed, for example, in the diffusion of alternative innovations, when only one of them can be established (e.g. magnetic video and digital tapes) or in the spread of influence of two opposing political forces. The results of the simulations below provide some insight into these issues.

Random network simulations have shown that in case of two opposing norms, full spread occurs in at least 4 and maximum 15 periods and the mean time of full spread varies from 7 to 7.6, depending on whether two randomly selected members have opposing views or two members with unequal positions, one of which is more connected, rather

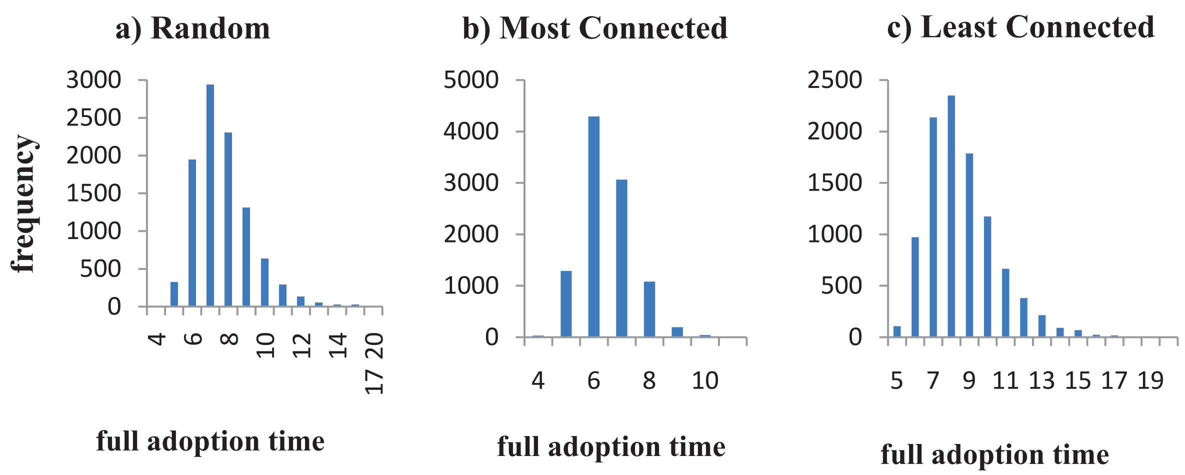
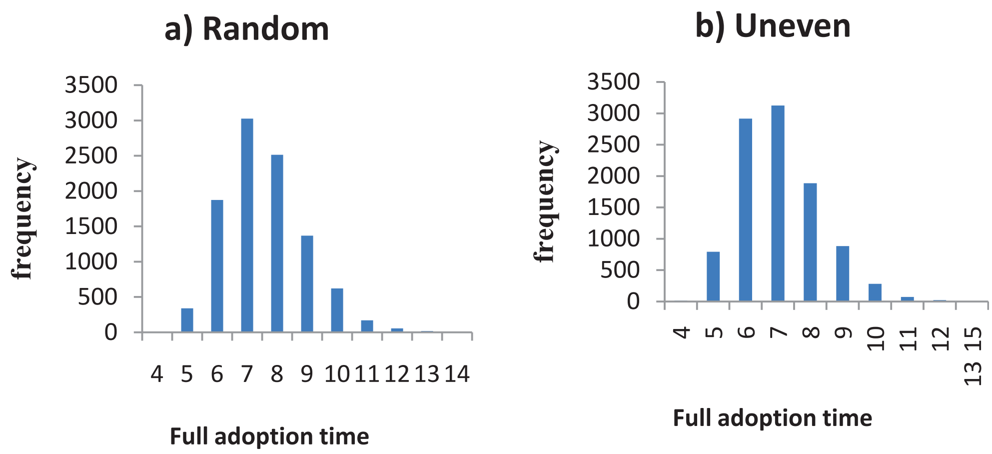


Figure 2. Results of simulations in small world networks when propagation starts from a) random member; b) most connected member; c) least connected member

Figure 3. Results of simulations in small world random network, when to opposing views are being spread from a) randomly chosen members; b) the most and the least connected members.



than the other. In 36.67% of the symmetrical cases one of the opinions was completely dominated, while in the other cases both views were maintained at different ratios. When one member was more connected than the other, complete dominance occurred in 42.19% of the cases.

In the case of two opposing norms in a single network, full adoption occurs at a minimum of 8 and a maximum of 96 periods, and the average adoption time varies from 20 to 25.6. Such extreme variability in the time of full adoption of a norm is due to difficulty of covering large masses when disseminating from the highly connected members of the network. Moreover, in 32.88% of the symmetrical cases one of the opinions was completely dominated, while in the remaining cases both were maintained at different adoption levels. When one opinion was spread from better connected member than the other, complete adoption occurred in only 1.15% of cases. This is due to the specificity of one-hub network. In this case, some peripheral members never adopt widely accepted opinions. Full adoption happens in multi-hub network over a period of 3 to 57 periods and the average time of full adoption ranges from 3.9 to 7.1. In 85.59% of the symmetrical cases one of the opinions was completely dominated, while in the asymmetric cases the complete adoption occurred in 53.98% of the cases. In a two-component network, full diffusion occurs in a minimum of 5 and a maximum of 20 periods and the average time of full adoption varies between 9.8 and 10. In 34.14% of the symmetrical cases one of the views was completely dominated, while in the asymmetric cases it was only 2.88%.

It is evident from the simulations that the position of the individual in the network is important to determine his or her impact on community or a particular group. It is no less important to know what type of network is best suited to represent a society and what the permeability of different norms, innovations or representations is within it. A central position of a member gives him a greater chance of dissemination of an opinion in the group but does not rule out the delay or failure of the process. In some cases the opinion of a less connected individual may be more successfully disseminated and established.

Group behavior spreads more rapidly in a random network than in a network characteristic of a special society on average. But multi-hub network has the potential for the fastest spread (although information disseminates faster in a random network on average). Group behavior is slow to spread in a single-hub network, as some individuals are very weakly connected to other areas of the network. An opinion spread in the neighbourhood of the central figure will soon reach all members of around him or her but it will take a long time to reach far ends of the network. The two-component network in this regard maintains a balance between the speed of distribution and the area of distribution. There is least variation between adoption times in a two-component network (not considering the small-world random network). The high variation in single-hub and multi-hub networks indicates that it is advisable to consider more specific situations for accurate results.

The computation of betweenness centrality indices revealed that the random network characterized with the lowest betweenness centrality coefficients from 0.002 to 0.051, while the one-hub network is naturally the highest - from 0 to 0.688.

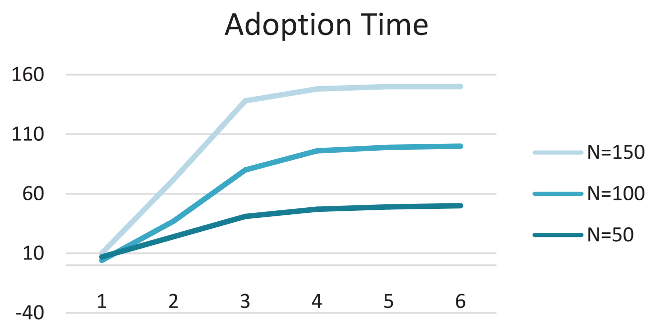
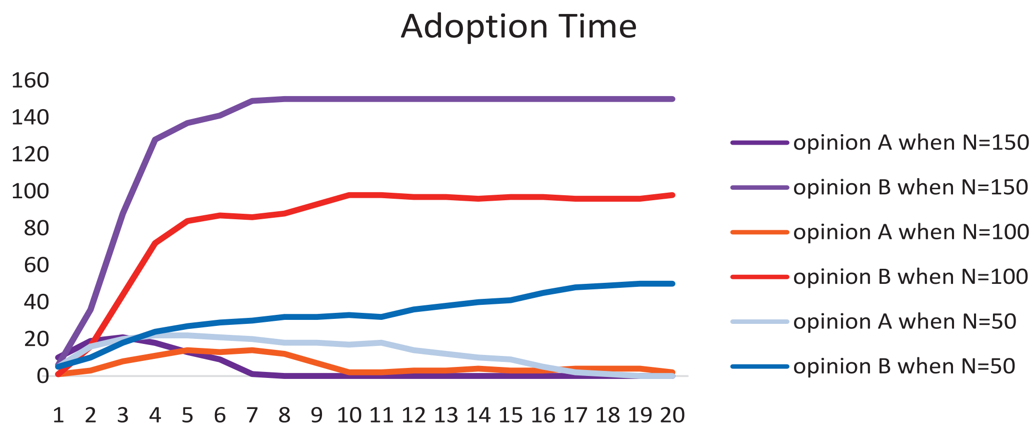


Figure 4. Adoption times in multi-hub networks of different sizes.

Figure 4 compares adoption times within multi-hub networks of different size and it is clear that adoption happens at the same speed most of the time regardless of the network size. In case of N=150 adoption is fastest and it takes only 5 periods. When two opposing opinions are being spread, the process reaches stability at different speeds. The next figure summarizes the results. When one of the opinions is dominated by the other, it takes similar time periods for all sizes of multi-hub networks but in this case the medium-sized one takes the longest to reach stability, while the network with 150 members stabilizes the fastest.

Figure 5. Adoption times for spread of two opposing opinions within multi-hub networks of different sizes.



It will be interesting for the future research to study adoption of group behavior from not one but multiple sources. Also, observing the distribution of group behavior across different network types, taking into account different model types and comparing the actual data with the given model.

CONCLUSION

The present paper analyzes patterns of information flow across different types of networks and compares the conditions for the emergence of group behavior. Simulations were carried out on 4 types of networks of 150 members - small-group, single-hub, multi-hub and two-component networks. According to the results, group behavior, innovation, opinion or norms can be spread within the network at different speeds.

In small world, full adoption occurs in 4-20 periods and the average time of full adoption is 6.5-8.6. In non-random propagation simulations, the highest and lowest degrees were selected according to the degree of dig. On the other hand, considering the betweenness centrality of CBl calculated for each member, the individuals with the highest and lowest values were chosen. In the case of a single-hub network, full adoption can happen very quickly or very slowly. The existence of one central figure prevents the spread of information across the network from the effect of preferential attachment and some members can only acquire a single link. If there are several central figures, the full spread is, on average, the fastest. It only takes 3.9-14.9 periods.

The study of the diffusion of two opposing views is interesting when dissemination of alternative innovations or spread of influence of two opposing political forces are studied. Conducted simulations show that in the case of two opposing norms, full propagation occurs most quickly within a multi-hub network with only 3.9-7.1 periods required on average and it is slowest in a single-hub network with 20-25.6 periods. The complete dominance of one of the opinions is highest in multi-hub network, where it occurs in 85.59% of symmetric cases and in 53.98% of asymmetric cases.

It is evident from the simulations that the position of the individual in the network is important to determine his or her the impact on a community or a particular group. It is no less important to determine the type of a network and the permeability of different norms, innovations or representations within. A central position gives a member a greater power in disseminating an opinion, but does not rule out delay or failure of the process. In some cases, opinion of a less connected individual may be more successfully disseminated and established. The size of a single-hub or multi-hub networks does not drastically change adoption times but can still have a small impact.

REFERENCES:

1. Braha, D. (2012). Global Civil Unrest: Contagion, Self-Organization, and Prediction. PLoS ONE 7(10): e48596. doi:10.1371/journal.pone.0048596
2. Feld, S. L. (1981). The Focused Organization of Social Ties. American Journal of Sociology, 86, pp. 1015–35.
3. Haveman, H. A. (1993). Follow the leader: Mimetic isomorphism and entry into new markets. Administrative Science Quarterly, 38, pp. 593– 627.
4. Jackson, M.O. (2011). An overview of social networks and economic applications. In: Benhabib, J., Bisin, A., Jackson, M.O. (Eds.), Handbook of Social Economics (Elsevier Press, Amsterdam), pp. 511–585.
5. Jackson, M.O. (2019). The Human Network: How Your Social Position Determines Your Power, Beliefs, And Behaviors. Pantheon.
6. Latané, B. and L'Herrou, T. (1996). Spatial Clustering in the Conformity Game: Dynamic Social Impact in Electronic Groups. Journal of Personality and Social Psychology, 70, pp. 1218–30.
7. Lieberman, M. B. and Asaba, S. (2006). Why Do Firms Imitate Each Other? Academy of Management Review, Vol. 31, No. 2, pp. 366–385.

8. Mazalov, V. V. and Chirkova, J. V. (2019). Networking Games: Network Forming Games and Games on Networks, Academic Press, 1st ed., pp. 155-161.
9. McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. Annual Review of Sociology, 27, pp. 415–44.
10. Merton, R. K. (1957). The Role-Set: Problems in Sociological Theory. British Journal of Sociology, 8, pp. 106–20.
11. Valente, T. W. (1996). Social network thresholds in the diffusion of innovations. Social Networks, 18(1), pp. 69–89.
12. Watts, D. and Dodds, P. (2007). Influentials, Networks, and Public Opinion Formation. Journal of Consumer Research, 34(4), pp. 441-458.
13. Young, H. P. (2006). The Spread of Innovations through Social Learning. Working paper, Center on Social and Economic Dynamics, Brookings Institution.
14. Xie, J., Sreenivasan, S., Korniss, G., Zhang, W., Lim, C., and Szymanski, B. K. (2011). Social consensus through the influence of committed minorities, Physical Review E, 84(1) 011130.

JEL Classification: D83, D85, D91 https://doi.org/10.35945/gb.2019.08.021

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SUMMARY

This paper aims to compare spread of an opinion, norm, innovation or a belief in different types of networks. For this purpose, different network metrics are discussed and results of network model are summarized based on simulations. Norms may spread from a single source or multiple sources and these issues require separate analysis.

Networks play an important role in decisions that people make. They determine what information someone will receive and how will he act within this limited information. As it turns out, small number of people can influence decisions of majority. These can be consumption decision, decisions about adopting new technologies, innovations, medical practice, social norms and so on. Mathematical models of networks help us understand how these processes propagate. There are different types of networks that can emerge within a society or some group and there are characteristics that can describe roles of group members in spreading some idea or innovation.

Networks can be of many kinds but human networks tend to have common characteristics. Therefore, current work focuses on 4 types of networks - small world, single-hub (one central figure), multi-hub (many central figures) and two-component. Small world random networks are observed in different situations and they can be used to describe some human interaction networks. Many networks are described by power law distributions, where new members of a network have a preferential attachment and link to other highly connected members. Single-hub and multi-hub networks describe such situations. Two-component network is used to describe polarized groups that have opposing views and are competing with each other. This could be political parties or competing firms.

The present paper analyzes patterns of information flow across different types of networks and compares the conditions for the emergence of group behavior. Contribution of this work is the simulation results that show how different networks exhibit varying outcomes and propagate opinions differently.

Simulations on small world, single-hub, multi-hub and two-component networks with 150 members show that network types matter in terms of how fast can group behavior spread within a network. The process of spreading group behavior is as follows: Every individual receives some signal si about a binary decision. Individuals make the first decision based on their signals because they have no other information. In the next step, every individual looks at the decisions of those in his or her neighborhood and updates his or her belief by the Bayes rule. On the next step they observe others' actions again and decide whether to change own action or not and so on. After some stages, a stable point is reached where no one is willing to change his decision anymore. The study compares the times needed to reach stability in different types of networks.

Simulations have shown that the speed of propagation of a belief varies according to who is the source of this process. However, the difference is not big within a small world network. As it turns out, full distribution occurs in at least 4 and a maximum of 20 periods, and the average time of full distribution varies from 6.5 to 8.6, depending on whether the most connected member is the source or the least connected one. The result is quite different if there is one central figure. The presence of one central figure prevents information from spreading across the network, as there is preferential attachment and some members can only acquire one connection. If there are several central figures, the full spread occurs relatively faster. In a two-component network, full adoption occurs quite rapidly. Although the connection between components is almost non-existent, a small number of existing links play a critical role in rapidly disseminating a behavior.

Group behavior spreads more rapidly in a random network than in a network characteristic of a special society on average. But multi-hub network has the potential for the fastest spread (although information disseminates faster in a random network on average). Group behavior is slow to spread

in a single-hub network, as some individuals are very weakly connected to other areas of the network. An opinion spread in the neighbourhood of the central figure will soon reach all members of around him or her but it will take a long time to reach far ends of the network. The two-component network in this regard maintains a balance between the speed of distribution and the area of distribution. There is least variation between adoption times in a two-component network (not considering the small-world random network). The high variation in single-hub and multi-hub networks indicates that it is advisable to consider more specific situations for accurate results.

Comparison of adoption times within multi-hub networks of different size shows that adoption happens at the same speed most of the time regardless of the network size. When two opposing opinions are being spread and one of the opinions is dominated by the other, it takes similar time periods for all sizes of multi-hub networks.