A MODEL OF DIFFUSION PARAMETER CHARACTERIZING SOCIAL NETWORKS

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ABSTRACT

We introduce a new diffusion property to characterize different models of social networks; the “Degree of Diffusion $\alpha$”. The degree of diffusion $\alpha$ introduced in this work is a totally new parameter. It relates the ratio of adopters over the non-adopters to the penetration depth in a diffusion process over a social network. It predicts the future possible adopters within any diffusion process. Each social network model is found to have a different diffusion characteristic value: Random $\alpha=148$, Small-World $\alpha=4.56$ and Scale-Free $\alpha=1.50$. A case study of a Real Social Network (Virtual Friendship Network) is found to have a value of $\alpha=29.58$ which characterizes the network to be between Random and a Small-World network models.

KEYWORDS

Diffusion, Social Network, Adoption rate, Penetration depth, Bimodal map

1. INTRODUCTION

Social sciences focus on the structure of different groups such as human groups, communities, markets, societies or the entire world system (Degenne & Forse 1999). A social structure is a network of social ties and a social network is on the other hand a set of individuals, organizations or other social entities connected by a set of social relationships, such as friendship, co-working relation and information exchange. Social network analysis assumes
that interpersonal ties are important, as the ties among organizations and countries, because they transmit behavior and attitude, information and goods. Social network analysis focuses on the analysis of the existing patterns of relationships and ties among social entities. The individual is not the basic social unit. The social atom consists of the individuals and their interpersonal social, economic, or cultural ties. Social atoms are linked into groups and interrelated groups and eventually form a society. Social network analysis might be applied on different social relationships and units. For example, Anthropologists study the kinship relations, friendships, and gift giving among individuals; Social psychologists focus on affections; Economists investigate trade and organizational ties among firms. In social network analysis, an individual is referred as an actor and we may say that social network analysis represents studying social actors and their ties (Degenne & Forse 1999).

There are several models for representing social networks such as mathematical models, graphical models (visualization), matrix models and statistical models (De Nooy et al 2005). The mathematical and the graphical models are mostly used by researchers to represent social networks. The mathematical model uses formal mathematical representations which allow the use of computers in analyzing the social networks. Also the mathematical techniques themselves may suggest things that were searched for in the data. The other model is visualization using graphs and using the graphical model to analyze a social network. In this model, graph nodes represent actors and edges represent ties among those actors. In this study, we use the graphical model along with the mathematical model to represent and characterize social networks. All generated networks are directed un-weighted graphs.

Assembling and gathering social network information is an important process. In order to assemble any social network, data must be collected about the actors and their ties. There are several ways for collecting data on social relations. We might ask people to write down the names of other people who they are related to in a group with respect to some specified activity. We also could use questionnaires, where the participants are able to write their choices or select among listed names. There are other ways such as fixed and free choice, ranking and paired comparison that are used through questioning to collect data for a social network analysis (Scott 2000).

Motivated to answer the question “Can we identify the type of a social network based on its diffusion behavior? and How?.” In this study, we introduce and test a new parameter, degree of diffusion, which solely depends on the network structure: actors and links. This property characterizes information diffusion within network and indeed helps to distinguish different types of networks. In other words, each social network model will be shown to have a degree of diffusion that differs from one another. We analyze the major model social networks the Random (RN), Small World (SW), and Scale Free (SF) then investigate and compare the type of actual virtual friendship social networks on the basis of the degree of diffusion.

2. DIFFUSION IN SOCIAL NETWORKS

The diffusion process is an important property of any social network. The diffusion process is the movement of information, diseases or innovations from one member to other members through social ties and relations within a social network. People are always interested in not acquiring contagious diseases, administrators are interested in diffusion of information and
market leaders look for distribution of new products. The diffusion process is very important in the social process since people always want either to disperse and spread their ideas and goods among the society or protect themselves from getting effected by harmful matters.

Diffusion in social networks is considered as a special case of brokerage that has a time dimension. Information, opinions and diseases are handed from one person to another person within a network in a course of time. In a social network, interpersonal relations are channels for social contagion and persuasion. The structure of the interpersonal ties is relevant to the diffusion process regardless of the characteristics of the actors. In fact, the characteristic of an actor does not make it more open to innovation than the others. The position of each actor in a network and its ties are the main factors that make it more open to the diffusion process. As an example, we consider the Kuwaiti society, which is a small and highly socially interconnected society. In this society, a Kuwaiti person could be an actor in several social networks such as family, colleagues, coworker groups, childhood friends, and etc. Individuals within those groups see each other so often and always share news, social matters and daily events. These strong interrelated ties among individuals within the group are sufficient to disperse a new technology among the group members. For example, assume that you are a person living in a Kuwaiti society and you meet a colleague at work and tell him about a technology such as the Bluetooth. He would go home and share the new information with his family members (Family group). Later that day, he might meet his friends at the coffee shop and tell them about the new technology (Friends group) and so on. Therefore, it is possible that within a short period of time, this new technology starts to spread among different groups of the society.

Most information diffusion studies focus on the factors that lead people to adopt or deny a new idea within a society (Young 2003). Others discuss the time dimension of the diffusion process in a sense that helps them toward discovering why some people adopt a new idea earlier and others take longer time (Young 2007). Several mathematical and network models are used to study the diffusion of innovations (López-Pintado 2004). A well known diffusion model is the Macro Model that is a mathematical model used to estimate the speed of diffusion and the rates of innovation and imitation. For example we can use this model to estimate the rate of disease spread from a central point such as contaminated food. Researches about diffusion have shown that the cumulative pattern of diffusion follows a growth pattern, which is represented as a one-parameter function shown below (Valente 2005):

\[ y_t = b_0 \frac{1}{1 + e^{-b_1 t}} \]

(1)

Where \( y_t \) is the proportion of adopters, \( b_0 \) is the \( y_t \) intercept, \( t \) is the time and \( b_1 \) is the rate parameter to be estimated. This model is a simple model used to compare the growth of innovation rates in various cases. This model is applicable for a small number of cases. Therefore, it is advanced and improved by researchers to produce a two-parameter model as follow (Valente 2005):
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\[ y_t = b_0 + (b_1 - b_0)Y_{t-1} - b_1(Y_{t-1})^2 \]  

(2)

Where \( y_t \) is the proportion of adopters, \( b_0 \) is the innovation rate parameter, \( b_1 \) is the imitation rate parameter. The new model includes the percentage adopters at each time point and thus provides a better estimate of the growth attributes in a personal network. The Macro Model could be used to (1) forecast expected levels of diffusion, (2) estimate the rate of diffusion according to external or internal influences (\( b_0 \) and \( b_1 \)).

The second model is the Spatial Autocorrelation, which measures whether artifacts, diseases and other behaviors spread between geographically neighboring areas rather than just estimating the diffusion rate. Data collection using such method is easy and thus providing a network of connections that is based on the distance between individuals. This method assumes that geographic closeness is same as communication and influence. Therefore, shorter distance between two nodes in a network means stronger communication and ties, which is not always true, particularly with the existence of mobile communication. Moran’s \( I \) is a special model developed to test the geographic clustering of adoption. Moran’s \( I \) measures the degree to which connected nodes in a network deviate from the average behavior of the overall network. The equation for Moran’s \( I \) is given below (Valente 2005):

\[ I = \frac{N \sum_i^N \sum_j^N D_{ij}(y_i - y)(y_j - y)}{S \sum_i^N (y_i - y)^2} \]  

(3)

Where \( N \) is the sample size, \( D \) is the distance matrix, \( y \) represents adoption and \( S \) is the summation of the distances in the distance matrix \( D \). The special autocorrelation was considered as a useful model for measuring network autocorrelation. Later studies showed that this model is not clear when used in measuring the diffusion process because it calculates diffusion at the macro level and does not show the effect of the nodes’ position in the network and the overall network structure on the diffusion process.

The Network Model is another model which overcomes the two problems of the special autocorrelation model. In this model each individual is connected to other individuals through social ties and relations forming a network of actors and relations where network influences are captured by an exposure model. In this exposure model, the degree of adoption of new innovations for each individual increases as the number of connected users in his/her network increase. Personal network exposure is the number of adopters within the network that provide influence and information regarding to some behavior. The equation for personal network exposure is given below (Valente 2005):
\[ E_j = \sum \frac{w_{ij} y_j}{\sum w_i} \]

(4)

Where \( w \) is the social network weight matrix and \( y \) is the adoptions vector. For an individual in a social network that has three contacts, \( E_j \) is the proportion of connected neighbors that have already adopted an innovation. The network exposure for direct contacts represents the social influence of individuals within the contacts through direct relation, persuasion or information transmission. The social network could be transformed to represent other aspects such as the degree of structural equivalence. For this type of network representation, network exposure captures the social influence through social comparison or competition. Network exposure also could be calculated using the network properties such as centrality where it represents the influence of a central point (opinion leaders) in the social network.

3. NETWORK MODELS

Three different network models are going to be analyzed in this study: Random, Small World and Scale-Free Network models. Each network model is created based on specific rules and might have different properties than the others. They all represent network models and all contain nodes and relations. In the following section, detailed description about the three main network models is presented in order to provide a better understanding of the structure of each network model.

3.1 Erdős and Rényi Random Network

One of the most popular models of random complex networks is the Erdős and Rényi model introduced in 1959 (Erdős & Rényi 1959, 1960, 1961). In this model, a network with \( N \) nodes is constructed along with a probability \( p \) for connecting each pair of vertices in the network, excluding duplicate or self-looping links (Costa et al 2006). The resulting network represents an Erdős and Rényi random network. Figure 1 represents an Erdős and Rényi network with 30 nodes and average degree of 3. In this study, we are going to refer to the Erdős and Rényi network model as the Random Network Model. There are other ways to create random networks such as creating \( N \) disconnected nodes and then creating \( M \) edges that are distributed randomly among pairs of nodes. The result will be similar for both procedures.
3.2 Watts-Strogatz Small-World Network

In 1967, Milgram made a famous experiment and found that two randomly chosen US citizens can reach each other through an average of six social links (Milgram 1967). He found that in a social network, everyone could be reached through a finite number of edge transitions (Watts 1999, Watts 2003). This concept is called the Small-World property, and therefore, a Small-World network model is defined as a network which has the Small-World property. Another property of the Small-World network is the existence of large number of loops of size 3 links, i.e. if node $a$ is connected to $b$ and $c$, then it is highly possible that $b$ and $c$ are also connected to each other forming a cluster of 3 links. A famous random network model, which satisfies the Small-World property and has high number of small clusters is the Watts-Strogatz (WS) small-world model (Watts & Strogatz 1998). To create a (WS) small-world network, we start with $N$ nodes, where each node is connected to $2k$ closest neighboring nodes in the network. At next stage, each edge in the network is rewired based on a rewiring probability $p$. The resulting network looks similar to the network shown in Figure 2, for a network of 30 nodes, $k=2$ and $p=0.3$.

In this study, we refer to the (WS) small-world network as the Small-World network. As shown in Figure 2, each node is connected to 4 other nodes ($2k$) through directed links and note that the applied rewiring concepts does not change the number of outgoing links from each node.
3.3 Barabasi and Alberts Scale-Free Network

Many studies had shown that the degree distribution for real social networks do not follow a unique pattern, instead it follows an uneven distribution. Barabasi and Alberts (1997) showed that in many systems, there are few nodes in the network that are highly connected while the others have much less connections. These few highly connected nodes represent hubs in the network and they attract a large fraction of the existing relations in the network. A network with the mentioned characterization is called a Scale-Free network. Scale-Free networks are built following a growth pattern. First, the network starts with a random network of size $M_0$. Then, the network grows by adding new nodes to the existing population and creating relations between the newly added nodes and some of the pre-existing nodes. Adding a new relation between a new node $i$ and an existing node $j$ is proportional to the total in and out degree of node $j$. The probability of creating a link between node $i$ and node $j$ is represented by the summation of all in and out degrees of $j$ over the total degree for the network (Bollobás 1998) and is given below:

$$p_{i \rightarrow j} = \frac{\sum \text{Degree}(i, out)_j}{\sum \text{Degree}(i, out)_{\text{network}}}$$

(5)

The higher the degree of $j$ is, the more possibility for $j$ to get new relations will be (rich gets richer) (Barabasi & Alberts 1997). When creating a scale-free network, two main parameters must be specified, $M_0$ and $p$. $M_0$ is the initial randomly created population of nodes with their random set of links and relations and $p$ is the connecting probability that will be used to determine whether a newly added node will be connected to an existing node or not (i.e., if $p_{i \rightarrow j} \geq p$, then a link between $i$ and $j$ will be created). Figure 3 represents a scale-free network with 30 nodes, $M_0=30\%$ and $p=0.1$.

![Figure 3. Barabasi and Alberts Scale-Free network with 30 nodes, $M_0=30\%$ and $p=0.1$](image)

As shown in Figure 3, all the nodes are connected in the network and no isolated nodes exist. This is a result of having relatively smaller connecting probability $p$. Also you can notice that there are four hubs like nodes in the middle of the network that almost every other
node is connected to. These nodes tend to have highest total degree when the network was initialized and therefore, they had attracted more relations toward them when the network was constructed and new nodes were added.

4. SOCIAL CONTAGION AND THE DEGREE OF DIFFUSION MODEL

One way of studying the diffusion model is to consider the effect of having opinion leaders and early adopters in a social network. These early adopters are assumed to be able to spread an innovation among their contacts through their social ties and relations. The second level of adopters are then assumed to pass on the innovations to their neighbors, where they will in turn pass it to their own neighbors and so on. In this model, diffusion is considered as a contamination process just like the spread of an infectious disease. It is also called Social Contagion (Scott 2000). Many studies showed that diffusion of innovation follows an empirical pattern similar to the process of spreading an infectious disease. An innovation is first adopted by few people, then their numbers increase relatively fast in the early stages until a huge number of people are infected (adopted the new innovation). Finally, the percentage of adopters decrease rapidly at late stages until the diffusion process completely stops and the adoption percentage converges to a unique value. In this study, we will introduce and calculate a new diffusion characterization parameter named the “Degree of Diffusion $\alpha$”. This parameter is going to be used in defining each network’s type along with predicting the proportion of future adopters over non-adopters at any given penetration level through the diffusion process.

4.1 Penetration Depth and Adoption Rate

The diffusion process follows an empirical pattern similar to spreading an infection among people. Starting by a single infected source, the innovation/disease is dispersed to the neighbors of the source at the first level. Then, each new adopter is going to spread the innovation/disease to its neighboring nodes at the next level and the infected neighbors are going to pass the innovation/disease to their neighbors. This process is repeated until possibly all the nodes in the network are infected and adopted the innovation/disease. Figure 4 provides a representation of the diffusion process when starting at different randomly selected sources.
Figure 4. Penetration depth for a network with 20 nodes and two randomly selected sources

In Figure 4(a), the source is shown at level 0 and its direct neighbors are indexed to 1 and the neighbors’ neighbors have index of 2 and so on. The last adopters are indexed to 4, which means that after 4 levels of receiving and forwarding (diffusing or dispersing information), all nodes are contaminated. The diffusion process is stopped at this level and no more nodes are going to adopt the innovation. The diffusion process stopped at level 4 even if some nodes that have not yet adopted the new innovation exist in the network.

The Maximum Penetration Depth $n_{\text{max}}$ is defined as the maximum distance between a source of diffusion and the last adopters in the network. For example, in Figure 4(a), the maximum penetration depth was 4 when started at that specific source. The maximum penetration depth for the network of Figure 4(a) might have been different if a different source was selected. In the previous example, the source was selected randomly and it was found to
be at the center of the network with more neighbors and relatively larger degree. Assume that the diffusion started at a marginal source, which is placed at the borders of the network with less number of neighbors comparing to a central source. The resulting maximum penetration depth is going to be 6 steps as shown in Figure 4(b). This means that the distance between this selected source and the last infected node(s) is 6 links and is larger than the previous case when a central source was selected. In both cases, the final percentage of adopters \( Y_n \) is equal to 95% of the total population. A single node exists with no connections to or from it and will not receive any information from the rest of the infected nodes (node is marked with a penetration depth \( n=99999 \) indicating that it is not connected and will not be reached).

![Figure 5. Adoption rate for the network with 20 nodes and two different selected sources](image)

The adoption rate curve, shown in Figure 5 represents the percentage of adopters at each penetration depth versus the penetration depth. Two different sources were chosen for the analysis. The solid curve represents the adoption rate when choosing a central source, as shown in Figure 4(a), and the dotted curve represents the adoption rate when choosing a marginal node as the source, as presented in Figure 4(b). Both curves have a typical S-shape with maximum penetration depth of 4 and 6 levels respectively.

### 4.2 The Degree of Diffusion \( \alpha \)

Thermodynamically, each penetration depth represents an equilibrium stage in the network between two phases: adopters phase and non-adopters phase. In equilibrium, stage \( n \), the simplest possible formulation is that the adopters are proportional linearly to the non-adopters, with a proportionality constant representing the equilibrium relevant to stage \( n \) and \( n+1 \) that can be expressed as:

\[
Y_n = K_{\alpha} (1 - Y_n)
\]

(2)
Equations (2) and (3) are the basis to define the degree of diffusion $\alpha$ as the ratio of the equilibrium constants at two back to back stages, $\left( \frac{K_{n+1}}{K_n} \right)$. Thus, it is a measure to predict the future adoption rate on the basis of the previous adoption rate in a diffusion process. In other words:

$$\alpha = \frac{K_{n+1}}{K_n} = \frac{Y_{n+1}/(1-Y_{n+1})}{Y_n/(1-Y_n)}$$

(4)

In addition, equation (4) is rearranged to express the future adoption rate in term of the previous adoption rate as given bellow:

$$Y_{n+1} = \frac{\alpha Y_n}{1 + (1-\alpha)Y_n}$$

(5)

Next, we numerically find the degree of diffusion $\alpha$ for a diffusion process in model and actual social networks. First, we start with the construction of a social network model (or actual social network). Second, randomly select an initial node (source) and calculate the percentage of adopted nodes, assuming anyone connected to the source will be an adopter. Third, the diffusion is then processed for the next levels of penetration along with calculating the percentage of adopters and so forth. In every penetration depth, we evaluate the adoption percentage using equation (5). Fourth, a set of data is generated, adoption percentage versus penetration depths. Finally, the set of data is fitted into equation (5) by means of non-linear regression to find the degree of diffusion $\alpha$. The non-linear regression is performed using the following objective function to get the final value for $\alpha$:

$$\text{Minimize} \sum_{n=0}^{N-1} \left( Y_{n+1} - \frac{\alpha Y_n}{1 + (1-\alpha)Y_n} \right)^2$$

(6)

Where $Y_{n+1}$ and $Y_n$ are the future and present adoption percentage. The former procedure is repeated for different source points; all nodes in the network are tested. As a result, $\alpha$, the average degree of diffusion, is resulted for the studied network. To get $\alpha$ for a single source of diffusion, the adoption rate is calculated for this chosen source. Algorithm 1 represents the detailed steps for finding $\alpha$, $Y_n$ and $n$, starting at a given source $S$. 

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Algorithm 1. Algorithm for calculating $\alpha$, $Y_n$ and $n$ for a selected source node $S$

5. RESULTS AND DISCUSSION

Sets of experiments are conducted to analyze the adoption rates along with the degree of diffusion values for Random, Small-World and Scale-Free network models. A Real Social network, represented by a Virtual Friendship network is analyzed and compared with the existing models. In the following sections, the applied experiments are described in details and the results are presented along with concluding remarks.

5.1 Experimental Results

The first set of experiments study the adoption rate in Random networks. A Random network with $N=50$ nodes is used, and the resulting adoption rate curves are shown in Figure 6(a). The resulting adoption rate curves follow the S-shape with different rates since the network is randomly generated and has random relations between nodes. The maximum penetration depth is $n_{max}=4$ with an average value of $n_{avg}=3$. The curves in Figure 6(a) show that the adoption rate is increasing rapidly at the early stages and it will converge to a unique value after the 2nd and 3rd steps respectively. As shown in Table 1, $\alpha$ for this network is found to be 148 and it spans for randomly selected different initial sources between 20 and 1000.

In the second set of experiments we study the adoption rate in Small-World Networks. For the Small-World model, two extra parameters are specified to conduct the experiments: the
total number of neighbors $2k$ and the rewiring probability $p_r$. A small-world network with $N=50$ nodes is used with $k=2$ ($2k$ total neighbors for each node) and rewiring probability $p_r=0.5$. The adoption rate curves are given in Figure 6(b) with a maximum penetration depth of $n_{max}=7$ and an average value of $n_{avg}=6$. The adoption rate curves show that nearly all the nodes have similar properties since the curves are almost identical with small difference. The experiments provide that the adoption rate is similar when starting at any random source within the network. The resulting $\alpha$ for different nodes fall between a minimum value of 3.4 and a maximum value of 6. The average degree of diffusion for this network is calculated and equals to $\bar{\alpha}=4.56$, as shown in Table 1.

The third set of experiments study the adoption rate in Scale-Free Networks. For such networks, two extra parameters are specified to conduct the experiments: the percentage of initial random population $M_0$ and the connecting probability $p_c$. A scale-free network is used with $N=50$ nodes, $M_0=0.4$ (40% of the initial population is randomly created) and $p_c=0.06$. The adoption rate curves are given in Figure 6(c) with an average penetration depth of $n_{avg}=3$. The adoption rate curves follow the S-shape similar to the random and small-world models. They converge to 0.4, which is the value of the initial population ($M_0=0.4$). The convergence occurs only after 3 levels of penetration. This is a predicted result since the initial population is randomly created and contains nodes with larger degree, forming a central partition in the network where all links are attracted toward it. This will lead most of the newly added nodes to be connected to the nodes within the initial population. For the scale-free model described above, the average degree of diffusion is 1.50, with $\alpha$ spanning in a narrow range of 1.11 and 1.67 for different randomly selected sources, as presented in Table 1.

The last set of experiments is conducted on a Virtual Friendship Social Network with 2393 nodes, representing a real social network with actual ties among individuals was analyzed to find its average degree of diffusion value. The resulting adoption rate curves are shown in Figure 6(d), with a maximum penetration depth $n_{max}=7$ and an average penetration depth of $n_{avg}=6$ levels. The test resulted an average degree of diffusion of $\bar{\alpha}=29.58$ for all selected nodes, with $\alpha$ values varying between 5.72 and 99.87, as shown in Table 1.

<table>
<thead>
<tr>
<th>Network Model</th>
<th>$\bar{\alpha}$</th>
<th>Range ($\alpha_{min} - \alpha_{max}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>148</td>
<td>20 - 1000</td>
</tr>
<tr>
<td>Small-World</td>
<td>4.56</td>
<td>3.40 - 6.00</td>
</tr>
<tr>
<td>Scale-Free</td>
<td>1.50</td>
<td>1.11 - 1.67</td>
</tr>
<tr>
<td>Real Social (Virtual Friendship)</td>
<td>29.58</td>
<td>5.72 - 99.87</td>
</tr>
</tbody>
</table>
5.2 Discussion

As described in the previous sections, several experiments were conducted to study the adoption rate in different network models such as Random, Small World, Scale-Free and Real Social (virtual friendship). The degree of diffusion for the different network models are summarized in Table 1, showing each network model with its average degree of diffusion and $\alpha$ range. The results show that the value of the average degree of diffusion for each network is related to the network size. For a random network, the average degree of diffusion increases exponentially along with the increase in network size, while for the small-world and scale-free networks the average degree of diffusion converges to some constant value. Therefore, for the first three models (Random, Small-World and Scale-Free), networks with size $N=50$ nodes were chosen. The selected virtual friendship network has a size of $N=2393$ nodes. Figure 7 shows the values of $\alpha$ for 50 selected sources of each network model. The resulting $\bar{\alpha}$ for the virtual friendship social network falls between the small world and the random network models (Mahdi et al 2009). Figure 7 illustrates the degree of diffusion $\alpha$ characterizing all different models discussed in this study.
The bimodal maps represent the relation between the future and the current adopters within the network models. For each network model, the corresponding bimodal map is constructed by substituting the value of $\alpha$ from Table 1 into the model equation (10), calculating the predicted values for future adopters percentage with respect to the current adopters percentage. Both Figures 7 and 8 are introduced to compare the virtual friendship network with the other network models. It is clearly observed that the resulting $\alpha$ and the bimodal map for a virtual friendship network falls between the Random and the Small-World network models. Due to the global aspects of the Internet, participants of a virtual friendship network can select their friends from remotely located cities and maybe continents. This plays a part in forming the random characteristics of such networks. However, as human being nature, people usually tend to select their friends from their neighboring vicinity, and this explains the small-world characteristics of those networks.
6. CONCLUSION

A newly proposed characterizing property for social networks is introduced based on diffusion principle. We coin the property the Degree of Diffusion $\alpha$. The parameter is found to have a unique value for each social network model discussed; Random, Small-World and Scale-Free. A Virtual Friendship network’s degree of diffusion is determined and its average value equals to 29.58. It suggests that such network is somewhere between a Random and a Small-World network. We refer to as "Random Small-World". We conclude that a virtual friendship social network is not purely small-world network as been suggested in the literature however; it is small-world with randomness implicitly existing in its topology.

REFERENCES