The Emotional Promulgation of Social Norms in Social Networks Based on Structural Properties

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Abstract— **Social norms play an important role in regulating the behavior of societies. They are behavioral standards that are considered acceptable in a group or society and violating them will result in sanction to violator. Both governments and various cultural communities use this social component to solve various problems in society. The use of norms leads to a large reduction in community spending to control harmful behaviors. Social norms have two important aspects of promulgating and sanctioning. They are promulgated by activists in the community and, after creation, are endorsed with a sanction. Norms can be used to promote a variety of different behaviors. Online social networks have established a new and influential platform for promulgating social norms. We first redefined the Rescorla-Wagner conditional learning model in the context of social norms with the help of a norm's intrinsic properties, and extract the main coefficients in the Rescorla-Wagner model related to it. Based on this model, we extract a network structure related parameter (i.e. clustering coefficient) for any individual in the social network to promulgate the norm with the conditional learning method. In this paper, by using the intrinsic properties of norms, we use and tune the Rescorla-Wagner conditioning model in order to obtain a new model for social norm promulgation. Based on this, we define criteria for the amount of effort required to promulgate norms in social networks. We show that there is negative correlation between the amount of effort required by each node to promulgate a norm and the clustering coefficient of that node. This result can be used to devise effective algorithms for social norms evolution.**

Keywords- social network; social norm; classical conditioning; clustering coefficient; Rescorla-Wagner

I. INTRODUCTION

The rapid expansion of social networks has made these networks one of the most important social organizations in the world today. In this space, millions of human beings can engage with each other to create new ideas and develop economically and culturally [1]. Social norms, as one of the most important components of community culture, can use this important opportunity to be promoted. Social norms are behavioral standards that are accepted by a group or community. Acting contrary to these standards will result in individual punishment. Social norms are also interpreted in the grammar of society [2]. The norms determine what should be done and what should not be done and are categorized in either a prescriptive or proscriptive manner [3]. Norms play an important role in advancing the goals of societies, especially the regulation of behaviors [4], [5], [6]. Norms are similar to rules and regulations, but they lack formal forms such

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as law. There are two categories of informal enforcement mechanisms: personal enforcement and community enforcement. In personal enforcement, fear of sanction prevents the person from acting and in community enforcement, social pressure and fear of sanctions prevent people from acting. Social norms are in second category. The recent category is related to social norms, and the sanction forces people to obey social norms [7]. The use of norms is widespread, which in many cases prefers to use instead of laws [8] or physical punishment [9].

The problem of the emergence and development of norms is one of the axes of the efforts of scientists in different fields. Online social networks have become an important platform for this evolution [10], [11], [12].

On the one hand, the creation of a social norm needs to be promulgated and, on the other hand, social pressure and sanctions to deal with its violation [3]. Social norm evolution in the social network can be based on these two pillars. The two pillars are also expressed in the macro-model by Coleman [13]. From the point of view of Coleman, the norm is a macro system that begins with the actions of individuals from the micro level and forms on a macro level, and then remains at the micro level through sanctions and punishments [13]. These steps are described below:

Step one: Performing individual actions to create the norm.

Step two: The formation of the norm in society.

Step three: individual sanction and Norm guarantee by sanction.

Any norm evolution model in social networks should cover the first and third stages of the above steps (promulgation and sanction). We will cover only the first stage in this article, and the third stage can be the subject of another research. In the first step, by examining the property of the norm, we seek to define a specific type of action that a person can convincing another person to obey the norm. At the end (third) stage after formation of the norm, we seek to prevent the violation of the norm through sanctions. In this research, we will present a new model for our first part and we propose a strategy for online social networking developers.

In our proposed model, the idea is based on the conditional learning or classical conditioning. Learning is a process that changes the behavior of individuals [14]. This method has many application in the field of psychotherapy and changes in negative habits and individual behaviors [14]. Here, the promulgation of the norm is carried out with the help of the conditional learning of the neighbors by influential people with high social capital. After learning the individuals, they will respond unconsciously upon request to comply with the norm. We seek to find a way in which the least effort is made to propagate the norm by the normative node in a social network. In the research, by looking at the properties of the norm and the components related to the network structure (here the clustering coefficient), we use the classical conditioning based learning method and associative theories for the norm.

In this method, which is called Pavlovian conditioning, there are the following components [14]:

a) An unconditional stimulus (US) that causes a natural and automatic response to the organism

b) A non-conditional response (UR) that is a natural and automatic response from the US

c) A Conditional Stimulator (CS), which is a neutral stimulant and does not cause a natural and automatic response to the organism.

d) A conditional response (CR) that occurs after several times running CS and US simultaneously.

When these components occur in a certain way, a conditional response (CR) appears. To create CR, you have to run CS and US several times. First, the CS and then the US. The arrangement of these two triggers is very important. Every time the US occurs, a UR is given. Eventually, the CS can be presented on its own and will call the UR-like answer. When this happens, a CR is created.

A good definition of the above model is provided by Epstein. The definition is as follows [15]:

Definitions

US: unconditioned stimulus [food]
UR: unconditioned response [food- induced salivation]
CS: conditioned stimulus [bell]
CR: conditioned response [bell- induced salivation]

Initialize

CS (bell) alone $\rightarrow$ 0 (no response)
US (food) alone $\rightarrow$ S (salivation)

Associative Learning

CS–US pairing trials: bell/food, b/f, b/f . . .

When Conditioned: B alone$\rightarrow$ S . . . CR = UR

This definition is based on the experiment of Pavlov's dog conditioning. The bell was also played at the same time as feeding dogs to release saliva. After several concurrency, when the bell was only played, the dog's saliva also secretes.

One of the famous models developed in this area is Rescorla-Wagner model. The equation defined in the Rescorla-Wagner model is as follows:

$$\Delta V_n = \alpha_A \beta_B (\lambda - V_{n-1}) \quad \alpha_A, \beta_B > 0 \ (1)$$

In this equation, the learning obtained before the nth try is shown with V_{n-1}; and learning change as a result of conditioning in n^{th} try is determined by ΔV_n. The symbol Δ is the change in V [14].

In equation (1) we have two important components α_A, β_B. α_A is potential Strength of associations of CS and β_B is potential Strength of associations of US. For example, a loud sound from an unobtrusively quiet sound has a higher value of α_A and a strong electric

shock from a weak shock causes a more reflective retardation; hence, it has a greater β_B value [14].

This equation shows that the change in the conditional learning power in each effort is a function of the difference between the maximum possible learning (λ) and the amount of learning that has been made at the end of the previous effort [14]. In this equation, the value of λ is asymptotic and the curve of the equation has a negative acceleration.

We use this equation for social norm. In this regard, we have calculated for α_A and β_B definitions that are proportional for social norms. We have defined that the potential Strength of associations of applying a norm by a higher social capital node in a social network is more than the potential Strength of associations of a person with lower social capital in that network.

Also, the potential Strength of associations of a norm can vary according to the extent of the need for that norm in society. In our model of research, we considered this coefficient to be the same for all norms. Considering the model of Rescorla-Wagner and the new conceptualization of the coefficients of this model in favor of the concept of norm, we obtain the relation between the amount of effort to infect the network to the norm and the clustering factor. This connection states that each node having more clustering coefficients with less effort can convince its neighbors to the norm. This result can be used to design the norm propagation algorithms.

The stages of this paper is shown by flowchart in Fig. 1.

II. Related Works

The general related research areas in this context are social contagion [16], [17], spread of influence [18], [19], diffusion of innovation [20], and cascading behavior [21]. The spread of different types of information between various nodes in networks and proposing algorithms is main issue in these articles. These mechanisms generally can be used for social norm promulgation.

Related to social norm promulgations, much research has been done by Berkowitz et al. [22]. Their research includes ways to solve challenges like sexual violence, alcoholism and smoking in schools and universities. They have called this approach under name of Social Norm Approach (SNA) where positive aspects of adopting a norm are emphasized instead of prioritizing negative aspects such as fear. For example the result of this research shows that only 5% of men conduct sexual assault, and an effective way to control this 5% is to make use of the other 95% percent [23]. After analyzing information of the problem, they run social campaigns to promulgate social norms in the context.

A proper related research that have focused on specific norms inside social networks is paper of "Norm evolution and violation on Facebook" presented by Caitlin McLaughlin et al. [24]. This paper use Expectation Violation Theory (EVT) [25] to analyze and extract social norms related to ethics of social interactions and activities in Facebook.

Social networks are also a fast and cheap medium for promulgating social norms. Researchers in [11], [12] use this medium to promulgate social norms related to controlling the spread of the HIV virus in societies and health projects and campaigns [26], [27].
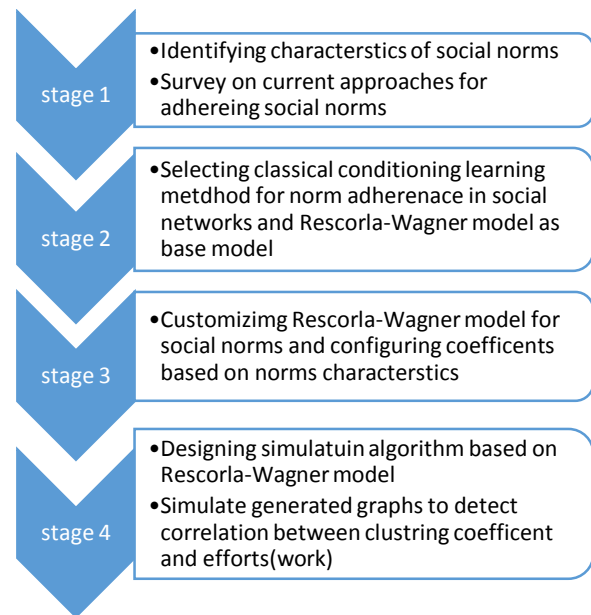

stage 1
- Identifying characterstics of social norms
- Survey on current approaches for adhereing social norms

stage 2
- Selecting classical conditioning learning metdhod for norm adherenace in social networks and Rescorla-Wagner model as base model

stage 3
- Customizimg Rescorla-Wagner model for social norms and configuring coeffecents based on norms characterstics

stage 4
- Designing simulatuin algorithm based on Rescorla-Wagner model
- Simulate generated graphs to detect correlation between clustring coefficent and efforts(work)

Figure 1. Stages of this paper

What we emphasize in this paper is the evolution of social norms by configuring and utilizing the social networks' properties. Much research has been done on developing behaviors in social networks. Alex Petland et al. from MIT's Media Lab [10] utilize behavior analysis methods in networks. Setting social networks so as to decrease the speed of dissemination of ideas so as to prevent herd behavior in choosing strategies and approaches is one of the most important technology based methods used by them for changing behaviors [23].

The research done by Zhang et al. is the nearest work to the findings of our paper which shows that nodes with higher degrees and lower clustering coefficient show more conformity to norms [28], but similarly to the other above examined works, does not take into account the intrinsic properties of social norms as we do in this paper.

Another category of researches in this context is steady-state analysis for adhering norms in social network Steady-state Analysis of a Neural-cognition Based Human-social Behavior Model [29]. In this category, the authors of this paper, have presented a new mathematical model based on Rescorla-Wagner model and Markov chain process, and formulated the problem of maximizing the adherence to a social norm in a social network by finding the best set of initial norm adopters. They proposed a linear programming algorithm for solving this problem that runs in polynomial time [23]. Difference between this work and [23] is that in this paper we only inference a new proposition that say which nodes in a social networks are proper for selecting to spend cost and budget and what is role of structure to spread norms in social

networks. In [23] we present a new, novel and optimized algorithm to adhere all nodes to a social norm. Summarily we are looking to discover a strategy to help create the norm. We intend to prove that if nodes with more power are selected and learn the norm, then with less cost and effort we can reach the norm. Paper 24 is close to our approach, but the difference with our method is that it does not pay attention to normative properties, but we pay attention to the inherent characteristics of the norm.

III. PROPOSED MODEL

Space Social norm disposition is a gradual process [5], [30], where the ability of a social node in making its neighboring nodes accept a social norm is related to the amount of effort (number of tries) that the aforementioned node applies [15]. If, in time t, we define $R_i(t)$ as the resistance threshold for each node i to accept a social norm, and also $D_i(t)$ as the amount of its disposition to accept a social norm, then that node accepts the social norm when:

$$D_i(t) - R_i(t) \geq 0 \qquad (2)$$

Different factors need to be considered when calculating $R_i(t)$ such as a node's position in the network structure. In this paper, we use the concept of social capital for this purpose and the criteria proposed for social capital in [31] which is called a node's power. There are many criterion and for simplicity we use only two important criterion that have positive effect on social capital. Equation (3) defines the simplified definition.

$$Power(i) = Betweenness(i) + Degree(i) \quad (3)$$

This is in accordance with [13] which states that a node's power has a direct correlation with its resistance to accepting a social norm. $D_i(t)$ is composed of the following components whose sum can be used to calculate disposition [15]:

$V_i(t)$: The emotional component

$P_i(t)$: The cognitive component

$S_i(t)$: The social component (social pressure and punishment)

Here, we limit our model to consider only the emotional component. As we previously saw in Colman's model for social norm individual actions play a vital role in increasing a node's disposition to accept a social norm. To model such actions different methods have been proposed, from Marginal Utility Theory [13] to Game Theory [32], [4]. In our model, we use Epstein's intuition in using Rescorla-Wagner conditioning theory for disposition's emotional component. Similarly other research have also used the theory of Rescorla-Wagner to propose neuro-computational models and their applications in social norm creation [33].

Here we define ΔV_n in Equation (1), as the increase in disposition to accept a social norm in the nth try compared to the $(n-1)^{th}$ try. The components of this model are redefined in the context of social norms as bellow:

- Unconditional Stimulus (US): Social norm promulgation action e.g. posting content in an online social network composed of the norm, a description of its benefits and consequences of the norm's sanctions

- Unconditional Response (UR): The disposition induced by the US

- Conditional Stimulus (CS): The acceptance of the social norm promulgation action by other nodes e.g. liking the post on the social norm

- Conditional Response (CR): The disposition induced by the CS

In accordance to [15], when the US and the CS are repeated simultaneously for a number of times the nodes in the network are conditioned so that after a while (e.g. based on the power of the person posting the content and the people liking the post) the US is not needed and the desired effect (disposition towards accepting the norm) is achieved by using only the CS.

As can be seen in Equation (1) the values for α and β must be calculated for each node. Social norms, as a type of cultural phenomena, make use of different transmission mechanisms to spread, including the following four [27]:

- Content-based transmission: copying others' content and subsequently transmitting them because of different characteristics of the content itself like its quality (γ_c).

- Model-based transmission: transmitting others' information or imitating their behavior under their influence e.g. based on their role (γ_r).

- Assortative transmission: imitating others because of a peer relationship with them e.g. being the same sex, having the same age, having the same religion, etc. (γ_p)

- Frequency-based transmission: if a large number of members of a society adhere to a behavior other members are put under pressure to imitate such a majority (γ_f).

In the Rescorla-Wagner model, α and β represent the strength of association in conditioning. To define these two parameters, we use the above mentioned variables. As we saw in our redefinition of the components of classical conditioning our unconditional stimulus is the action of promulgation, i.e. the content that is posted on social media and therefore the quality attributes of the content itself (social norm definition) is important. Also, conditional stimulus is the acceptance of this action which is directly correlated to factors such as the role of the nodes posting the content or liking it, its relationship to its peers and also the share of the network that adheres to the norm. Therefore α which is related to the conditional stimulus is equivalent to the sum of γ_p, γ_r and γ_f and also β which is related to the unconditional stimulus is equivalent to γ_c. Simplifying the quality of the US (content), for β we define a constant quality value of 1. Also for α we define three ranges based on the power of the nodes (actors) in the network as below:

$$\alpha = \begin{cases} 0.3 \ \ if \ the \ actor's \ power \ is \ low \\ 0.6 \ \ if \ the \ actors \ power \ is \ medium \\ 0.9 \ \ if \ the \ actors \ power \ is \ high \end{cases}$$

Our goal of providing the above parameters is simply to provide a vision for better understanding of the subject. In this paper, we use the simplest method for expressing the concept, and we only put forward the criteria for use. Therefore, considering the weight when it comes to meaning we want to accurately implement these mechanisms. The relative values considered for alpha are also for this purpose. And since its range is between zero and one, we have defined the thresholds for high power, medium and low power. Of course, we arrive at these approximate numbers in a simulated calculation whose graph is given below (Fig. 2).

The terms low, medium and high are interpreted according to how we define power. To illustrate this, consider the following example for an actor with high power (influence):

$\alpha\beta = 0.9, V_0 = 0, \lambda = 90, \epsilon = 0.01$
$try_1 : \Delta V_1 = 0.9(90 - 0) = 81 \Longrightarrow V_1 = 81$
$try_2 : \Delta V_2 = 0.9(90 - 81) = 8.1 \Longrightarrow V_2 = 89.1$
$try_3 : \Delta V_3 = 0.9 \ (90 - 89.1) = 0.81 \Longrightarrow V_3 = 89.91$
$try_4 : \Delta V_4 = 0.9 \ (90 - 89.91) = 0.081 \Longrightarrow V_4 = 89.991$
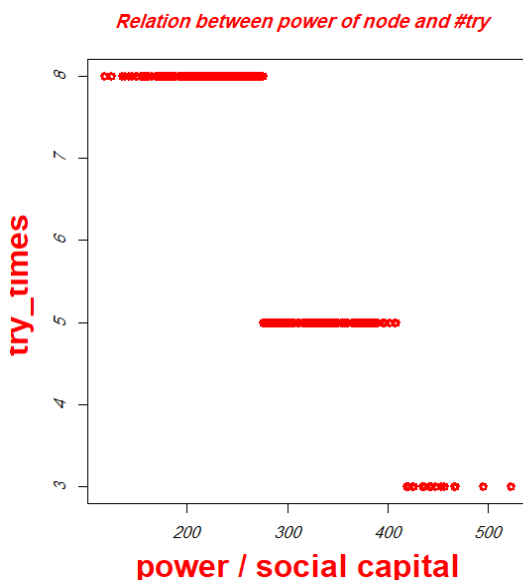$$\approx V_3$$

As can be seen, after the third try, conditioning takes place and from try_4 onwards the amount of added learning is negligible, i.e. $\Delta V_4 < \epsilon = 0.01$.

We can formulate the number of tries needed for a node to condition one of its neighboring node to adopt a norm.

For each node, we can calculate the number of tries needed for conditioning another node:

$V_n - V_{n-1} = \alpha\beta(\lambda - V_{n-1}) \Longrightarrow$
$V_n = \alpha\beta\lambda + (1 - \alpha\beta)V_{n-1} \Longrightarrow$
$V_n = \alpha\beta\lambda + (1 - \alpha\beta)[\alpha\beta\lambda + (1 - \alpha\beta)V_{n-2}] =$
$[\alpha\beta + (1 - \alpha\beta)\alpha\beta]\lambda + (1 - \alpha\beta)^2 V_{n-2} =$
$[\alpha\beta + (1 - \alpha\beta)\alpha\beta + (1 - \alpha\beta)^2\alpha\beta]\lambda + (1 - \alpha\beta)^3 V_{n-3}$
Iterating this process we have (assuming $V_0=0$):

Relation between power of node and #try

$$V_n = f(n)\lambda + (1 - \alpha\beta)^n V_0 = f(n)\lambda,$$

Figure 2. Graph to guess relative value of α

Where

$$f(n) = \sum_{i=1}^{n} \alpha\beta(1 - \alpha\beta)^{i-1}.$$

Thus we have,

$$\Delta V_n = \alpha\beta(1 - \alpha\beta)^{n-1},$$

So, if we take the stopping condition into account we have:

$$\Delta V_n < \epsilon \Longrightarrow \alpha\beta(1 - \alpha\beta)^{n-1} < \epsilon \Longrightarrow n$$
$$> \log_{(1-\alpha\beta)} \frac{\epsilon}{\alpha\beta} + 1 \quad (4)$$

As we show the number of tries is depended to α and α is related to power of a node in social network. If initially we adopt some nodes (by assigning enough budget) with high social capital (high power) to social norm, then we can promulgate social norm in proper time and with less effort. One of the best criteria for selecting proper nodes in a social network is clustering coefficient. The clustering coefficient and closure are two main structural properties of social networks [34].

Our method in this research is to calculate the amount of effort of each node in convincing all related nodes. Then we calculate the total volume of effort necessary to infect the network based on the sum of the nodes' effort. After this step, we analyze the relationship between the clustering factor and the amount of effort. This is done by simulation.

In this model, each node has its potential association, depending on its strength, with a coefficient α. On the other hand, each node has a resistance to accept the norm. Define the strength of each node as the average of the power or social capital of the network.

The simulation algorithm is such that, as soon as every effort based on Formula (1) is made to infect a node with the other node, the number of attempts of the active Node (Normative) is increased and the target Node resistance is reduced. If a node with other nodes has connections and those nodes are more closely related to each other (higher clustering), then naturally the number of attempts to convince that node over it will be greater and, as a result, Will be accepted for admission.

The simulation have been done on 10 different graph generated by Erdos-Renyi network model. The main reason to selecting this model was simplicity and frequently use of it in similar researches. The simulation results are as follows in Table 1.

Table 1. Ten different graph generated for simulation

Graph	Properties
1	V=250, E=2358, D=0.03, AVGP=71.58, AVGCL=0.34

2	V=270, E=2567, D=0.35, AVGP=77.48, AVGCL=0.33
3	V=300, E=2567, D=0.03, AVGP=90.31, AVGCL=0.33
4	V=220, E=2186, D=0.04, AVGP=59.8, AVGCL=0.4
5	V=400, E=7635, D=0.05, AVGP=108.22, AVGCL=0.41
6	V=210, E=1636, D=0.04, AVGP=64.15, AVGCL=0.33
7	V=370, E=1695, D=0.01, AVGP=171.57, AVGCL=0.13
8	V=528, E=4534, D=0.01, AVGP=87.23, AVGCL=0.26
9	V=410, E=5382, D=0.03, AVGP=80.92, AVGCL=0.40
10	V=400, E=5540, D=0.03, AVGP=59.22, AVGCL=0.53

Table 2 shows the simulation results on the graphs defined in Table1. By running a regression between the effort amount (work) of each node and the clustering factor in each ten graphs, we conclude that there is a negative correlation between the volume of the effort or the work done and the clustering factor of each node. The third column of the table below shows this negative correction. The major result of this simulation is that high-cluster nodes require less effort to create a tendency to neighboring nodes, and this results in a good strategy for designing the promotion algorithms. Also 5 graphs of performed simulations are below (Fig. 3 to Fig. 7).

IV. CONCLUSION AND FUTURE WORKS

In this study, we first explained, based on Coleman's model, that the norm as a macro-social system is based on individual actions and then sustained by sanctions. We used an emotional factor for one's actions and defined the Rescorla-Wagner conditional learning model the context of social norms, and then using simulations we were able to obtain the relationship between the clustering factor and the amount of effort necessary to promote the norm by a node among its neighbors. From this feature, we presented a strategy for promulgation, and showed that to reach a higher speed (less effort) in infecting a network with a desired norm, nodes with higher clustering coefficients should be selected. This model can be used for future research in the field of promoting other social interaction structures such as trust, authority and market exchange. Also, other factors such as cognition can also be used to discover how to enhance this method.

Table 2. *The simulation result on ten graph show negative correlation between cl and effort*

Graph	Rounds	Coefficients: (Intercept, clustring_coeff)
1	*50*	(87.27, -35.88)
2	60	(126.8, -136.8)
3	30	(164.5, -212.2)
4	40	(85.63, -57.33)
5	30	(189.1, -188.8)
6	30	(101.8, -100.5)
7	30	(247.2, -558.9)
8	40	(111.96, -82.75)
9	40	(121.34, -90.74)
10	30	(72.08, -17.55)
Analysis Result		There is Negative correlation between work(effort) and clustering
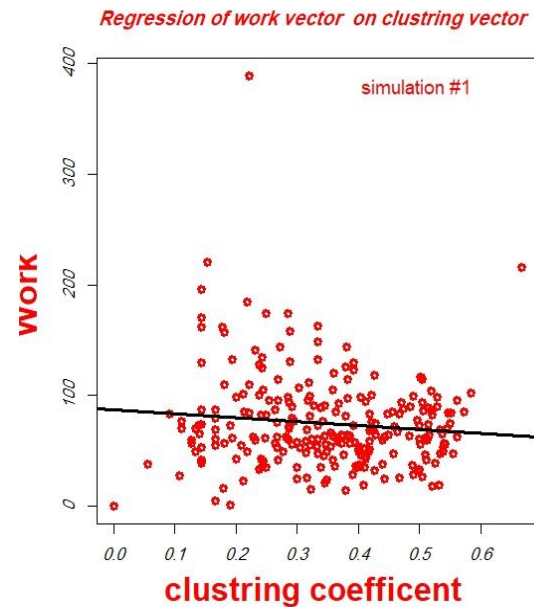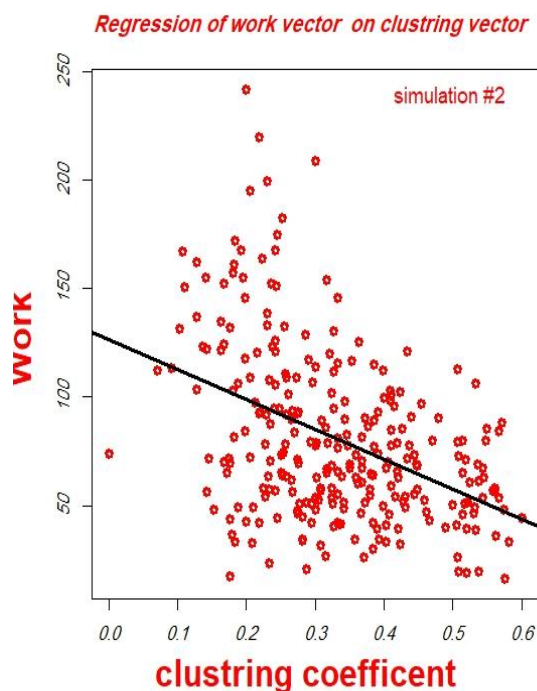
Fig. 3 *Graph of simulation #1*

Fig. 4 *Graph of simulation #2*
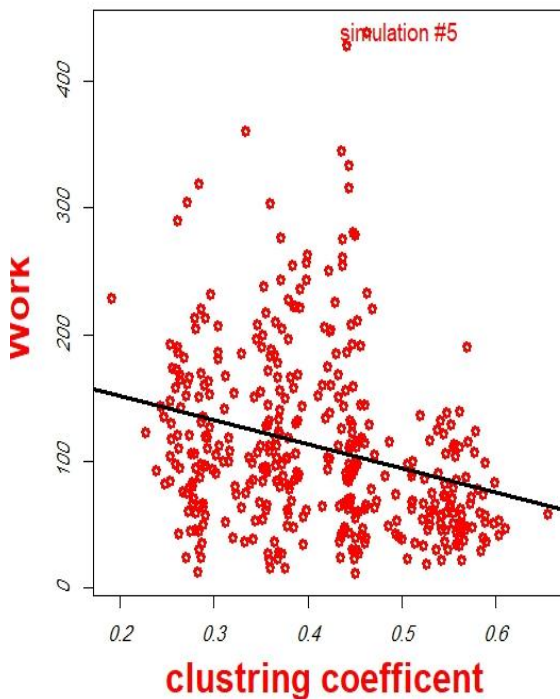
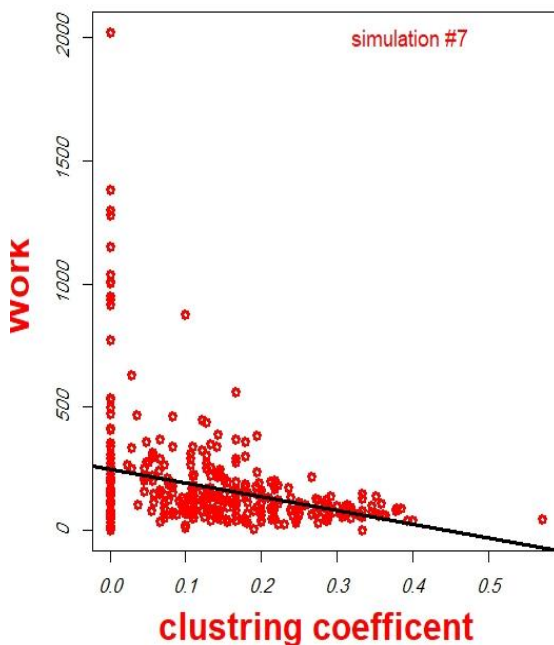*Fig. 5 Graph of simulation #5*

Fig. 6 Graph of simulation #7
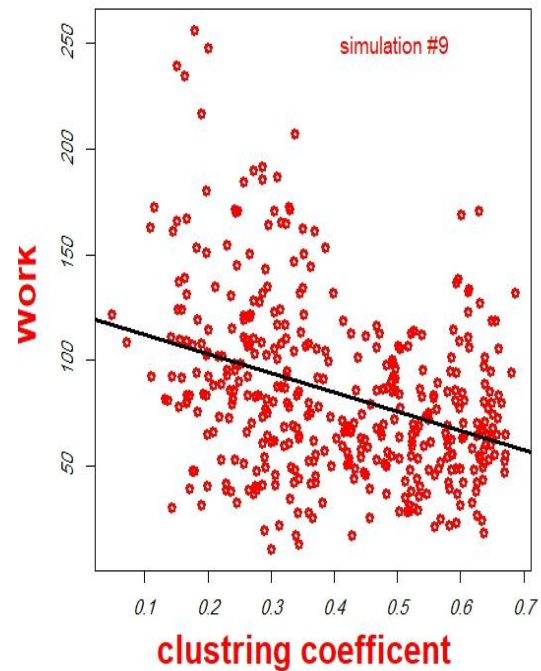
Fig. 7 Graph of simulation #9

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