Interdisciplinary Description of Complex Systems 11(3), 310-317, 2013

IMPACT OF OPINIONS AND RELATIONSHIPS COEVOLVING ON SELF-ORGANIZATION OF OPINION CLUSTERS

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DOI: 10.7906/indecs.11.3.1
Regular article

Received: 10 December 2012.
Accepted: 6 February 2013.

ABSTRACT

In a social network, individual opinions and interpersonal relationships always interact and coevolve. This continuously leads to self-organization of opinion clusters in the whole network.

In this article we study how the coevolution on the two kinds of complex networks and the self-organization of opinion clusters are differently affected by the dynamic parameters, the structural parameters and the propagating parameters. It is found that the two dynamic parameters are homogeneous bringing about the strong and weak relations, while the two structural parameters are heterogeneous having equivalent relations. Moreover, the impact of the propagating parameter has been found only above its threshold.

KEY WORDS

opinion cluster, coevolution, self-organization, opinion propagation, relationship evolving

CLASSIFICATION

JEL: D70, D84

PACS: 89.75.Da, 89.75.Fb

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INTRODUCTION

Opinions which individuals hold and relationships among them always interplay and interact, which can lead to self-organization of opinion clusters. The definition of opinion clusters has two: one is the sets in which individuals have the same opinion and the association among them [1, 2]; the other is the sets in which individuals also have the same opinion, but with or without association among them is no limited [3, 4]. The latter is employed in this article.

In social systems, the formation of opinion clusters is affected by many factors, such as diffusional dynamic parameters, network structural parameters and different network characteristics. As it is very difficult to study the social systems for the complexity of them, many researchers recently investigated the social system by networks [5, 6]. Many real systems, such as social systems, ecological systems, and cellular systems, can be represented as networks, in which nodes denote the objects of interest and edges that connect nodes describe the relationships between them [7, 8]. However, current researches for opinion clustering detection focus more on finding algorithms that can identify opinion clusters in all contexts [6-8], than on the effects of different factors on opinion clustering in the same context.

In this study, we simulate information propagation in different conditions on networks to result in self-organization of opinion clusters, in order to ascertain the effects of dynamic parameters, structural parameters and networks characteristics on it.

THE MODEL

Many discoveries [9-11] show that a number of large-scale complex networks, including the electric power grid for Southern California, the network of movie-actor collaborations, and the neuronal network of the worm Caenorhabditis elegans, are scale-free and small world. The Watts-Strogatz (WS) small world model exhibits a high degree of clustering as in the regular network and a small average distance between vertices as in the random network. The Barabási-Albert (BA) model suggests that the two main ingredients of self-organization of a network in a scale-free structure are growth and preferential attachment [10].

Let us consider opinion synchronous diffusion[1] on WS and BA networks.

OPINION MODEL

Each of N vertices denotes an individual and each of M links denotes a relationship between two individuals in the network. We consider O_i possible opinions of which every individual must hold one, and two relationships (called +1 and –1) denote positive sentiment (friends) and negative sentiment (enmities), according to balance theory. Opinion model in this study is the majority-friends-rule model extending the majority-rule model [12, 13]. It assumes that individuals preferentially follow the friends instead of following the crowd (the majority-rule[2]) in their opinion update. In each step, every vertex has the same opportunity to update its opinion or relations by the following rules:

1) majority friends' preference (MFP): with probability P, the focal individual accepts the specific opinion held by a majority of its friends (i.e., the opinion is the one or one of that has the largest supporter among the friends). If the specific opinion is more than one, random one of them is chosen. We call this process P action,

2) cognitive consistence (CC) [14]: with probability $1 – P$, the focal individual keeps his opinion unchanged and updates (keeps or flips) its relationship. It will keep the sign of edge if the focal pair is cognitive consistence: holding the same opinion with positive (+1) relation or different opinions with the negative (–1) relation. On the country, an edge will

flip the sign if the focal pair is cognitive inconsistence: the same opinion hold by focal pair individuals with negative (–1) relation or vice versa. When flipping is activated, with likelihood Q, the focal individual will flip all of links to neighbors, or with likelihood $1-Q$, it will flip random one of links to neighbors. We call these processes Q action and $1-Q$ action,

3) repeating previous two steps, the system will converge to consensus state. The consensus state has two sub-states: one is opinion consensus sub-state; another is relation consensus sub-state. They respectively represents that all opinions and all relations currently hold by all individuals do not change over time. After reaching the two sub-states, the system can only reach consensus state. It also claims that the coevolution between opinions and relations has been completed. The particular algorithm is shown in Figure 1.

PARAMETERS

The two networks (BA and WS) which have same parameters and scopes of parameters. The total number (N) of vertices is fixed ($N = 1000$, $O_i = 100$). There are three types of variables: structural parameters, dynamical parameters and diffusive parameter. Structural parameters include average degree $\langle k \rangle \in \{4, 6, 8, 10\}$, as well as a proportion of negative edge $P_{ne} \in [0, 1]$. Dynamical parameters include the probability of opinions propagation $P \in (0, 1)$, as well as the likelihood of relations evolution, $Q \in [0, 1]$. There is one diffusive parameter, the initial number of opinion clusters, $O_i \in \{100, 200, 290, 366, 433\}$. The final number of opinion clusters after evolution is O_f.

```
1  i=1
2  while (not opinion-consensus-substrate
      or not-relation-consensus-substrate)
3   foreach vertex
      with probability P, execute MFP
      with probability 1 –P, execute CC
    end foreach
4   if(i>=3)
5     if(Sign{vertices}i = Sign{vertices}i–1
        and Sign{vertices}i = Sign{vertices}i–2)
        opinion-consensus-substrate ← True
      else
        opinion-consensus-substrate ← False
6     if(Sign{edges}i = Sign{edges}i–1
        and Sign{edges}i = Sign{edges}i–2)
        relation-consensus-substrate ← True
      else
        relation-consensus-substrate ← False
    end if
7  i++
   end while
```

Figure 1. Main algorithm of opinions diffusion and relations evolution.

SIMULATION RESULTS

THE NUMBER OF OPINION CLUSTERS

It is similar on the self-organization of opinion clusters of BA (Figs 2a) and 2c)) and WS network (Figs 2b) and 2d)), because scale-free networks are also small-world networks [14], because (i) they have clustering coefficients much larger than random networks [11] and (ii) their diameter increases logarithmically with the number of vertices N [9].

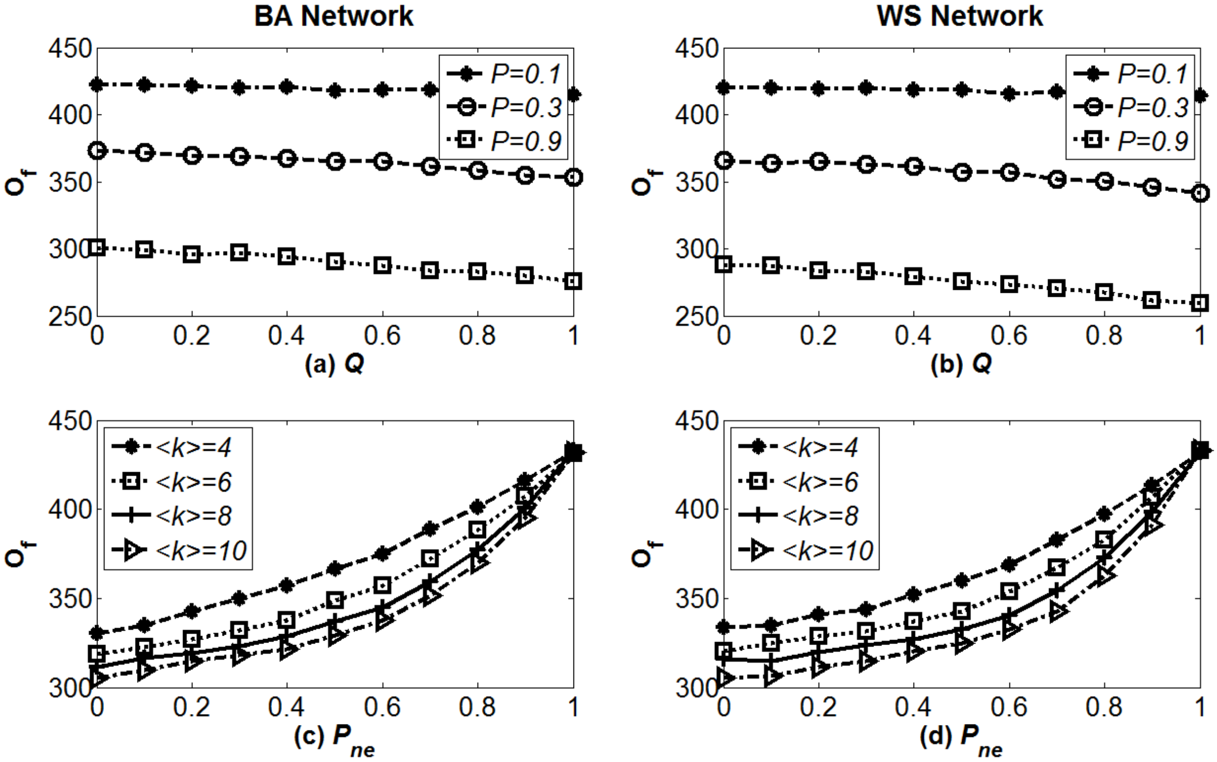

Figure 2. The effects of dynamical parameters, structural parameters and network types on the self-organization opinion clusters during evolution, with N = 1000. In a) and b) $\langle k \rangle = 4$ and P_{ne} = 0,5, while in c) and d) P = 0,5 and Q = 0,5.

The two dynamical parameters are homogenous to the process (Figs 2a) and 2b)). Both the P and the Q promote to self-organization and deduce the number of opinion clusters with the increasing of them. While the effect of P is larger than that of Q for the Q action occurs on the condition probability of 1 –P. As is shown in equation

$$\Pi(Q) = \Pi(Q \mid 1 - P) = (1 - P)Q. \tag{1}$$

However, the two structural parameters are heterogeneous in that the increasing of average degree $\langle k \rangle$ hinders the self-organization of opinion clusters. It is in contrast with the fact that increasing P_{ne} accelerates it. That indicates that the increase of edge density is advantageous to the density of the opinion clusters if the increases are of opposite signs. If P_{ne} = 1, opinion clustering cannot proceed, the number of opinion clusters will not cannot be inferred using the rule of MFP as it is almost invalidated, thus an individual in such a network has few friends.

THE RATIO OF SURVIVAL OPINION CLUSTER

The ratio the survival opinion cluster is denoted as R_{S}, $R_{\mathrm{S}} = O_{\mathrm{f}}/O_{\mathrm{i}}$ where O_{f} is the number of survival opinion cluster and O_{i} the number of initial opinion cluster. As shown in Figure 3, the difference of effects between BA and WS network on R_{S} is quite obvious. Under the same

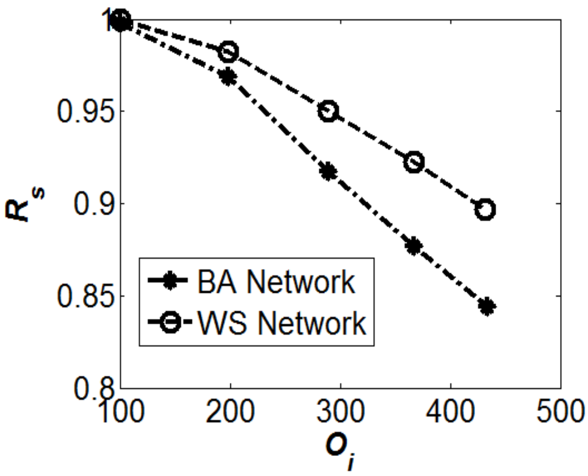

Figure 3. The effects of the types of networks and the number of initial opinions on the ratio of survival opinion cluster.

condition, R_S in WS network is larger than that in BA network. As O_i decreases, O_f always increases both in WS and BA networks.

If $O_i \leq 0{,}1N$ then R_S will reach 1 (thus all the opinion clusters will survive) whatever other parameters are.

THE SCALE OF OPINION CLUSTERS

In this section we analyze the effects of three types of factors on the self-organization of the opinion clusters, measured by the top 10 of opinion clusters' (abbr. top 10) sizes after coevolution. The average size of an opinion cluster is inversely proportional to the number of opinion clusters and is analysed further in the text.

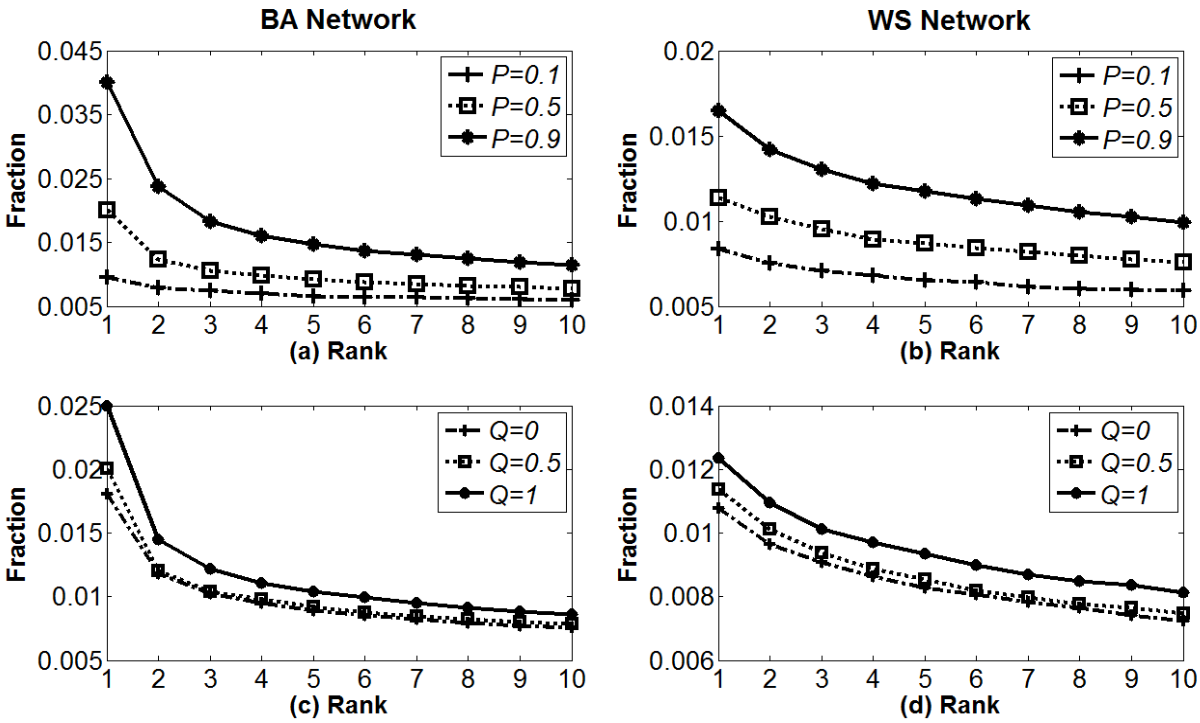

Figure 4. The effects of dynamical parameters on top 10 sizes. The rank of top 10 sizes versus the fraction of top 10 with a) and b) P equal to 0,1, 0,5 and 0,9 for constant Q = 0,5, c) and d) Q equal to 0, 0,5 and 1 for constant P = 0,5. In all graphs N = 1000, $\langle k \rangle = 4$ and P_{ne} = 0,5.

Figure 4 shows that top 10 sizes in BA network is always larger than that in WS network in most cases at the same condition. This is maybe due to that degree distribution of BA network is power-law and tendency to form bigger community (community is always opinion cluster under the rule of MFP, though not vice versa) than that of WS network which has average degree distribution.

The effect of structural parameters is that the sizes of top 10 are proportional to P and Q for constant values of other parameters. While the effect degree of Q is smaller than that of P, as shown in Figure 4 (three curves in Fig. 4c) and Fig. 4d) are mutually closer than the corresponding curves in Fig. 4a) and Fig. 4b)). The effect indicates that the bigger the P value, the greater the probability that each individual supports the popular opinion (the opinion which most of friends holding). It is a benefit that advantageous opinion clusters (top 10) enlarge advantages (i.e. top 10 have more supporters). The effect of Q is similar to that of P. If Q increases, the probability of advantageous individuals getting more friends also increases. It also results in the larger sizes of top 10. Whatever the way the Q action occurs in the condition probability $1 - P$, the effect of Q is usually smaller than that of P (except if P is relativelly very small and close to zero).

It is clear that structural parameters effect on the sizes of top 10: the sizes are proportional to $\langle k \rangle$ value and inversely proportional to P_{ne}. As $\langle k \rangle$ value rises, the clustering coefficients in BA and WS network both increase. It benefits advantageous opinion to increase supporter microscopically, thus larger sizes of opinion cluster form macroscopically.

On the contrary, with the increase of P_{ne} value, each individual will decrease its friends in microscopical scales, thus it also leads to advantageous opinion clusters decrease sizes in macroscopical scales.

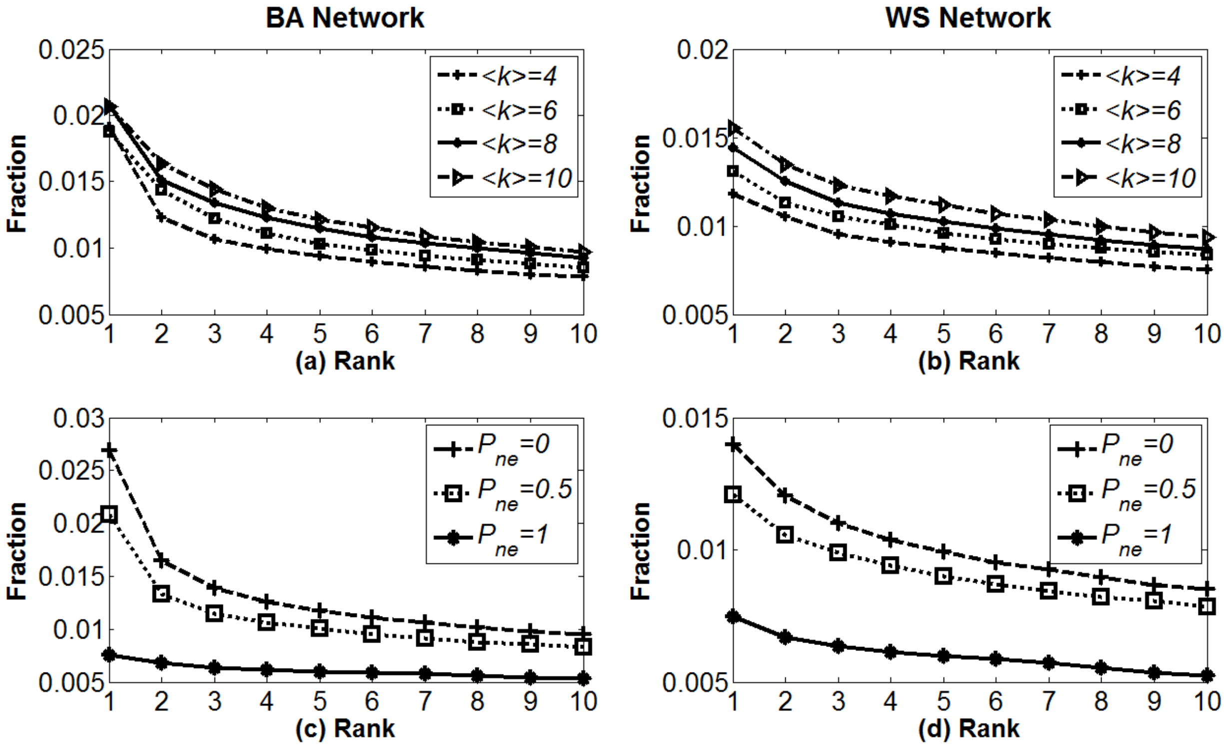

Figure 5. The effects of dynamical parameters on top 10 sizes. The rank of top 10 sizes versus the fraction of top 10 for a) and b) $P_{ne} = 0{,}5$ and $\langle k \rangle$ values equal to 4, 6, 8 and 10, c) and d) $\langle k \rangle = 4$ for P_{ne} values equal to 0, 0,5 and 1. In all graphs $N = 1000$, $P = 0{,}5$ and $Q = 0{,}5$.

CONCLUSIONS

In this article we investigated the effects of three factors (dynamical parameters, structural parameters and diffusional parameter) on the number and scale of opinion clusters. We found that the two dynamical parameters (P, Q) are homogeneous from the direction of effect on opinion clusters coevolution, and strong-weak relations from the degree of effect on it. The two structural parameters ($\langle k \rangle$, P_{ne}) is just opposite to the two dynamical parameters: they are heterogeneous and equivalent. Moreover, the number of opinion clusters in final stage is inversely proportional to the number of opinion in initial stage when the initial number of opinion is larger than threshold value. But when it is less than threshold value, the phenomenon disappears: the number of opinion clusters no longer changes. The phenomenon suguests that moderate number of opinions (less than threshold) facilate to propagate than excessive number of opinions, because some of excessive opinions can not survive during the process of diffusion under the control of some dynamic rules.

ACKNOWLEDGMENTS

S.L. Zhang acknowledges the support from Graduate Innovation Foundation of Southwest Petroleum University, GIFSB0707 and X. Sun acknowledges the support from Graduate Innovation Foundation of Southwest Petroleum University, GIFSS0727.

REMARKS

[1]Synchronous diffusion: each vertex updates opinion at the same time in order to ensure diffusion independent of the sequence of vertex.

[2]Synchronous diffusion by majority preference rule finally leads to a trivial absorb state that all of vertices holding the same opinion. So we employ majority friends' preference in this study.

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UČINAK KOEVOLUCIJE STAVOVA I VEZA NA SAMOORGANIZACIJU GROZDOVA STAVOVA

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SAŽETAK

U društvenoj mreži individualni stavovi i osobne veze stalno međudjeluju i ko-evoluiraju. Time neprestano dolazi do samoorganizacije grozdova stavova u cijeloj mreži.

U radu se razmatraju ko-evolucija na dvije vrste kompleksnih mreža i samoorganizacija grozdova stavova kao posljedica više dinamičkih parametara, strukturalnih parametara i parametara propagacije. Uočeno je kako su dva dinamička parametra homogena i vode na snažne odnosno slabe relacije, dok su dva strukturalna parametra heterogena i vode na ekvivalentne relacije. Učinak parametara propagacije uočen je samo iznad njihovih pragova.

KLJUČNE RIJEČI

grozd stavova, ko-evolucija, samoorganizacija, propagacija stava, evolucija veze