The “mutual ignoring” mechanism of cyberbalkanization: triangulating observational data analysis and agent-based modelling

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Abstract

Cyberbalkanization has been observed in some online activities, but its mechanism remains uncertain. Drawing on the Social Balance Theory, we theorized that the formation of “mutual ignoring” triads (three actors in a group with only a pair of interacts) in a network is a key procedure for cyberbalkanization. A cyberbalkanized network was constructed using data shared on Facebook Pages during the 2014 Hong Kong protests. Our findings indicate “mutual ignoring” was a prominent triad network configuration, whereas no such configuration was found in randomly generated networks. Our empirical-based observation was retested with simulation by agent-based model, confirming that “mutual ignoring” is essential for the emergence of cyberbalkanization. A strategy is then suggested to minimize cyberbalkanization.

Keyword: cyberbalkanization, social media, political communication, social network analysis

Introduction

Cyberbalkanization is known as “the phenomenon in which people seek out only like-minded others and thereby close themselves off from the ideological opposition, alternative understanding, and uncomfortable discussions” (Brainard, 2009). Hebenstreit (2014) defines cyberbalkanization as “division of users into groups that do not interact with each other.” One result is that online users with similar political ideology tend to group into isolated online communities. For instance, Twitter users exhibited a segregated bipartisan retweeting network structure, limited interactions across the two groups during the 2010 U.S. congressional midterm elections (Conover et al., 2011). Additional evidence suggests that opinion polarization on social media is issue dependent, i.e. polarization is only observed when information exchange is related to political issues (Barberá, Jost, Nagler, Tucker, & Bonneau, 2015).

Community formation plays a crucial role in the process of cyberbalkanization. Community in the social network analysis context is defined as collections of nodes with dense connections within a community and sparse connections with nodes outside the community (Newman, 2004). Sunstein (2009a) suggests that formation of communities in social media is harmful to democracy because users are exposed only to information that reinforces pre-existing beliefs and possibly cultivates political extremism (Sunstein, 2009b).

Even though the role of online community is recognized, the exact mechanism for cyberbalkanization has not been understood (Hebenstreit 2014). In this study, we suggest a better understanding of mechanism of community formation might be useful to developing an effective strategy for encouraging deliberative communications between communities and thus reduce the likelihood of political extremism.

Previous literature usually explains the formation of insular communities in a communication network with individual behaviors such as selective exposure (Iyengar, Sood, & Lelkes, 2012) and motivated reasoning (Levendusky, 2013). However, community formation is not purely a result of individual behavior and it is a collective result of interactions between individuals ¹. Therefore, we should examine what kind of interaction pattern between individuals gives rise to community formation. But it is often difficult to study these interaction patterns using only empirical data.

Empirical data analysis helps researchers study the characteristics of social networks, but it is rarely used to investigate the process or mechanism of specific phenomena. A triangulation approach is deployed by combining different methodologies to theorize, test, and retest social phenomena. In the current study, we conducted agent-based modeling (ABM) to simulate interacting actors in a network as an alternative approach to triangulate the study's conclusion drawn from observational data analysis (Bonabeau, 2002).

Online Communities and Cyberbalkanization

Internet communication appears to have the potential to promote communication between people with different backgrounds and also to facilitate communication between like-minded individuals. The latter properties of the Internet can strengthen online communities with common ideologies. Constrained human interactions can drive community formation (White, Boorman, & Breiger, 1976). Van Alstyne and Brynjolfsson (1996) theorized that new constraints in communication are no longer matters of geographical distance but of human capacities such as our limited capacity for calculation (Simon, 1957). In the context of online communication, despite the fact that the Internet is universally

¹ Otherwise known as emergent behaviour

accessible to people with different ideologies, netizens can only interact with a small set of contacts and often ignore, consciously or unconsciously, a vast majority of individuals with whom they are very likely to disagree.

Some online users can play a role as a “bridge” between communities. However, Castells (2011) suggest “switchers”, those who facilitate discussion and ensure cooperation between online communities, are rare and therefore online communities are usually insular with very limited interactions between members of different communities.

Van Alstyne and Brynjolfsson's theory of cyberbalkanization (1996) posits that a group of individual behaviors drive community formation in social networks and therefore community formation should be an emergent phenomenon that might be generalized into a model.

Community Formation in Social Networks

Currently, there are a number of models to explain community formation in the social media but each has limitations. The preferential attachment-based Barabási-Albert model (Barabási & Albert, 1999) reflects scale-free degree distribution but fails to model reciprocal directed edge formation. New models simulating mutual degree generation and community formation usually require defining system level parameters. For example, the preference memory network model (Li, Lu, Li, & Yu, 2013) generates social networks with coexisting scale-free, small-world high-clustering and short average shortest paths. However, the specification of an “interest vector” to quantify interpersonal compatibility among the agents in such a model is too simplistic.

There are two community formation models that focus on the generation of segregation in social networks.

A Model of Segregation Emergence

On the emergence of segregation in a social network, Henry et al. (2011) showed that even a small amount of bias resulting from being connected to others who are dissimilar to themselves leads to network segregation, a social-network analog to Schelling's model of residential segregation (1969). Node-level similarities were used in Henry et al.'s study to determine the probability of connecting other nodes, and they likewise showed that homophily processes (bias toward forming attribute-close relationships) are not a necessary condition for the emergence of network segregation. The model employed by Henry et al. has made an assumption about the existence of a node-level attribute(s), and his model only considers the reconfiguration of a nonsegregated network and therefore ignores conventional network generation mechanisms such as preferential attachment.

Social Balance Theory

Social Balance Theory, proposed by Khanafiah and Situngkir (2004), is another model of community formation which makes no assumption on homophily. This model in itself is based on Heider's Balance Theory (1946) as an explanation of the formation of two balanced and stable communities in a social network, otherwise known as social mitosis (Wang & Thorngate, 2003). Social Balance Theory suggests that the formation of the microstructure of balanced triads is essential for the formation of the global macrostructure of social mitosis. Balanced triads can be calculated by sentiment (which can either be positive or negative) among actors. Balanced triads can only be achieved when the sign multiplication of its sentiment charges positively. For example, a triad with three edges being positive, negative and negative is considered to be a balanced triad because positive (+) x negative (-) x negative (-) equals positive (+). There are only two combinations of three edges that result in balanced triads and they are: 1) positive, negative, negative and 2) positive, positive, positive.

Social Balance Theory assumes valued and undirected edges between nodes with the edge attributes being sentiment. Similar to the model of segregation emergence, Social Balance Theory does not take into account other network generation mechanisms such as preferential attachment.

Mutual Ignoring as a Generative Mechanism of Cyberbalkanization

In sum, the models used in current literature suffered from the following limitations: 1) ignoring community formation and cyberbalkanization; 2) making too many assumptions by means of specifying system parameters; 3) only applicable to specific cases, e.g. reconfiguring network or using in network with sentiment edges. We aim to formulate a parsimonious but realistic model of cyberbalkanization which maximize the generalizability while making least assumptions.

Drawing on the thesis of cyberbalkanization (Van Alstyne & Brynjolfsson, 1996) and Social Balance Theory (Heider, 1946; Khanafiah & Situngkir, 2004), we seek to test a set of agent behaviors collectively called “mutual ignoring” which make no assumption about node and edge attributes.

“Mutual ignoring” is the process of two friendly nodes simultaneously ignoring one or more nodes. Such social network configuration can be expressed as “102” in Davis and Leinhardt’s classification system (1967). The “102” configuration is a generalization of three out of the four balanced triads if we substitute edge formation as positive sentiment while no edge formation, i.e. ignoring, is seen as negative sentiment. (Figure 1)

We designed a study to examine the mechanism of “mutual ignoring.” First, we compared the likelihood of “mutual ignoring” formation in a cyberbalkanized social network with the controls, i.e. randomly generated networks. Second, we retested the generation of cyberbalkanization with ABM by simulating the interactions of Facebook Pages (agents).

We hypothesized that mutual ignoring is one of the key procedures for the genesis of

cyberbalkanization. We presented the statement into two congruent hypotheses for social network analysis and ABM respectively for triangulation purposes (Erzberger & Prein, 1997).

Hypothesis 1: Cyberbalkanized social networks have a higher likelihood to form “mutual ignoring” triads (“102” configuration) than do randomly generated networks (and even scale-free networks).

Hypothesis 2: A group of interacting agents with mutual ignoring behavior can generate social networks with isolated communities.

Methods

The study was divided into two parts.

Observational Study of Cyberbalkanized Social Networks

The first part of the study was designed to test Hypothesis 1. A Hong Kong Facebook Pages sharing network was constructed and used to examine the network characteristics of a cyberbalkanized network. Pilot run of data collection have been reported elsewhere (Chan & Fu, 2015) and current study is its extension to a full study. In essence, 2,983 Facebook Hong Kong-based public pages were sampled by using snowball sampling approach. The pages' publicly available posts between July 2014 and June 2015 were retrieved by Facebook Graph API. A post-sharing network was established with a node denoting one Facebook Page and a weighted edge representing sharing relationships between two pages, i.e. an edge weighting between two nodes is the total number of shared posts between two pages within the entire study period.

There are two reasons why this network dataset is appropriate for studying

cyberbalkanization: 1) previous studies have used networks of information sharing to analyze online polarization (Conover et al., 2011), and 2) the study period covered the period of the 2014 Hong Kong protests during which the city's political development was heat debated. In addition, a previous survey has found that Facebook use was associated with opinion polarization during the study period (Lee, 2016).

In total, 126,462 instances of content sharing were included. The log-log plot of the Facebook sharing network is presented in Figure 2 to show the network was scale free.

Large communities in the Facebook sharing network were determined using the walktrap community detection algorithm (Pons & Latapy, 2005). The reasoning for using this algorithm was based on the performance comparison conducted by Papadopoulos et al. (2012), who finds the walktrap community detection algorithm can detect more consistent communities in medium-size social networks ($< 10^6$ nodes) than others.

Modularity is an index to measure the strength of division between communities in a network (Newman, 2006). In this study, the modularity of the community structure determined by the Walktrap community detection algorithm was also calculated. A triad census of the Facebook sharing network was conducted to determine the proportion of the "102" triads. A triad census is a technique in social network analysis to summarize the microstructure of a social network by counting the frequencies of all triads of a network that fall into 16 possible configurations (O'Malley & Marsden, 2008). The microstructure of a social network as summarized by a triad census is usually compared with randomly generated social networks (Wasserman, 1977). The triad census from a random network produced by the Barabási-Albert model with linear preferential attachment (power = 1) was used as a benchmark to show the excess proportion of "102" triads in the Facebook sharing network.

The exponential random graph model is an alternative approach that could be deployed to test the same hypothesis in empirical social networks (Goodreau, 2007). This

method is not employed in the current study because the models generated were found to be unstable in social networks with more than 1,000 nodes (Schweinberger, 2011).

Simulation of Social Network Formation

The second part of the study aimed to test Hypothesis 2. An ABM framework was created to simulate the interactions of Facebook Pages. ABM is often used to simulate complex systems such as social network formation from the ground up by simulating the interactions between autonomous agents. Agents are programmed to perform specific tasks or behaviors, such as various modes of interactions between agents, and one possible goal is to study how a collection of individual behaviors affects system-level structure (Macal & North, 2010).

In the context of this study, the ABM was deployed to study how the behaviors of agents, such as performing “mutual ignoring” between agents, affect the overall community structure of the entire social network of agents, i.e. generating cyberbalkanization.

The agents in our ABM framework were named “faceboids” (Facebook pages-like agents) and their behaviors were modeled after Facebook pages. The model was initiated with the following system level parameters:

- Number of faceboids, $N_{\text{Faceboids}}$
- The maximum probability of being retweeted for each faceboid post, P_{MaxRT} . This parameter indicates the theoretical barrier in communication between agents. Lower P_{MaxRT} indicates a high barrier and vice versa.

All faceboids were initialized with a value of N_{RT} (number of retweets), which is randomly assigned by following the Poisson distribution ($\lambda = 50$). In every time step, each faceboid was programmed to perform two tasks: 1) randomly publishing $\text{Pois}(\lambda = 1)$ number of posts onto the public timeline, and 2) retweeting posts from the public timeline that had

been published in that time step. When a faceboid retweets a post, the N_{RT} of the posting faceboid increases by one.

The probability of a post being retweeted ($P_{retweet}$) was calculated using the following formula. Three parameters governed $P_{retweet}$: 1) the N_{RT} of the poster, 2) the maximum N_{RT} among all faceboids and 3) the P_{MaxRT} .

$$P_{retweet} = P_{MaxRT} \times \frac{N_{RT of Poster}}{Max N_{RT}}$$

As the $P_{retweet}$ depends on the number of retweets, this is a preferential attachment behavior.

On top of the default preferential attachment behavior, four “mutual-ignoring” agent behaviors were also included.

Each faceboid has memory to keep track of a list other faceboids it has retweeted. When a reciprocal edge is formed between two faceboids (i.e. they have ever retweeted each other), the mutual-ignoring behavior modes are triggered. Four modes of mutual-ignoring mechanisms are studied:

- Mutual random: Each of the two faceboids selects one faceboid that has not been retweeted and never was retweeted from that faceboid again.
- Mutual common choice: One faceboid was randomly selected from the union set of faceboids that had not been retweeted by both sides. Neither side ever retweeted from that mutual choice of faceboid again.
- Mutual common choice and sync: Similar to the mutual common choice, after adding one mutually chosen faceboid to ignore, all faceboids that had been ignored by both sides are combined and synchronized.
- No mutual ignoring: No mutual ignoring, preferential attachment only.

Using various modes of agent behaviors, the sharing networks created by the swarms of faceboids were analyzed using the methodology in the observational study described above. Their network characteristics were compared.

In this simulation, the number of faceboids was set to be 1,000 and the P_{MaxRT} were specified as 1/1,000, 1/10,000 and 1/100,000 respectively. Choosing 1,000 as the number of faceboids is based on pragmatic reason: it is the largest number that the simulations can finish in a reasonable time. It is hard to estimate P_{MaxRT} in a real-life dataset. One possibility is to estimate the observed probability of retweets for each Facebook page and select the highest one, but such probability might have been influenced by other social network properties such as preferential attachment. Because of this, we chose a very wide range of P_{MaxRT} and studied how this parameter affects the simulation results. We have tried higher P_{MaxRT} (1/10 and 1/100) but no community could be formed, and therefore we deemed $P_{\text{MaxRT}} \geq 1/100$ was too high to be realistic.

In total, twelve (4 modes of agent behaviors x 3 sets of P_{MaxRT}) experimental conditions were created and simulated. As a result, four simulated networks were generated. The number of time steps for each simulation was 365, i.e. one year. One-way analysis of variance was used to analyze the average modularities of four networks generated from the four types of agents.

We hypothesized that social networks generated from agents with mutual-ignoring behaviors have higher modularity than other generated networks.

Results

Social Network Analysis of a Hong Kong Facebook Sharing Network

A Hong Kong Facebook Pages sharing network was constructed. It is a scale-free

network as indicated by the log-log plot (Figure 2), indicating preferential attachment might be at work. Ten communities with at least 30 pages were extracted from the sharing network, and these communities roughly followed a grouping with similar political ideologies (Table 1). Using the community structure detected by the walktrap algorithm, the modularity of the Facebook sharing network was 0.213. The results of the triad census are shown in Table 2. The ‘102’ configuration was the third most common configuration (probability = 0.17%) and much higher than the expected probability from the random networks generated by Barabási-Albert Model.

Agent-based Modeling of Community Formation

The average modularities of simulated networks of each set of experimental conditions are shown in Table 3. In general, the modularities were lower in the simulated networks with a higher chance of forming connections as indicated by P_{MaxRT} . The agent behaviors made a nonsignificant impact on modularity except in the case of high probability ($P_{\text{MaxRT}} = 1 / 1000$) where “Mutual common choice and sync” agents yielded networks with a significantly higher level of modularity ($P < 0.001$).

Discussion

“Big data” analysis has often been criticized by social scientists as over-reliance on data-driven decision making, which reflects a lack of theoretical validity (Tufekci, 2014). The current study first drew on Social Balance Theory, then demonstrated a triangulation approach of combining the results generated by the ABM technique and network analysis, and finally testing the hypothesis on the generative mechanisms of network formations.

Based on the observations drawn from an empirical dataset of a cyberbalkanized social network in the context of contentious politics, the “mutual ignoring” triad configuration was found to be the third most common configuration in the triad census. Such

a configuration did not exist in the controls, i.e. randomly generated networks created by the Barabási-Albert random graph algorithm. This finding first established a possible mechanism that formation of “mutual ignoring” might be a necessary condition for cyberbalkanization.

The finding was then retested by triangulating with our ABM program faceboids, which aimed to test the hypotheses of community formation on Facebook. We found that mutual-ignoring behaviors on top of the preferential attachment were found to be significantly associated with the generation of social networks with more separated communities in the case of a low theoretical barrier in communication (high P_{MaxRT}), i.e. a higher chance of mutual communication between actors. In other words, even though social media can in principle enable mutual communication among groups, an individual’s choice of mutual ignoring markedly undermines the affordance of the social media and can collectively result in a set of community clusters among which less traffic is communicated across communities.

There are of course alternative explanations for mutual ignoring only affects community generation in the case of a low theoretical barrier in communication. When mutual ignoring was introduced, the generation of more modular social networks might be mediated through selective suppression of interactions and this alone can increase the modularity of social network. The effect of interaction suppression by mutual ignoring might have been not prominent when the theoretical communication barrier is too high (See Table 3).

The reason for mutual ignoring in social media warrants further study. Besides balancing sentiments among actors in triads as proposed by Heider’s Balance Theory (1946), we suggest that it might also be a result of limited attention of the Facebook page administrators (Weng, Flammini, Vespignani & Menczer, 2012). Administrators might only pay attention to a small set of pages and thus ignore a larger set of pages. A pair of pages

sharing stories with each other might indicate that they interest in a similar set of pages and thus ignore a similar set of pages. Also, algorithmic filtering of news feeds based on social network characteristics such as Facebook's EdgeRank algorithm² and "recommended pages" feature³ might encourage mutual ignoring and thus increase the likelihood of cyberbalkanization.

There are limitations in the current study. First, the homophily was assumed to be manifested only as retweet behaviors. The homophily of node level demographic characteristics (such as political ideologies, cultures and interests) was not considered in this study. We anticipated that inclusion of other homophily might make edge formation more selective than the random selection-based mutual-ignoring behavior because the probability of edge formation was even lower. Second, the faceboid simulation in this study did not take network growth into account. However, our software framework can be easily modified to introduce new nodes during the simulation. Third, many simulated networks generated from the faceboids simulation did not follow scale-free degree distribution which occurs with a real-life Facebook Pages sharing network. That is probably because preferential attachment is not the single mechanism that generates scale-free networks. A previous ABM study (Johnson, Faraj & Kudaravalli, 2014) has shown that a multimechanism model, including mechanisms such as least effort, direct reciprocity, and indirect reciprocity together with preferential attachment, was found to be the actual mechanism leading to the formation of a scale-free network. However, the current faceboids simulation only considered two sets of agent behaviors, i.e. preferential attachment and mutual ignoring, and hence was not sufficient for the consistent generation of scale-free networks.

² <https://www.facebook.com/help/327131014036297/>

³ <https://www.facebook.com/addpage>

Nonetheless, the contribution of the current study is both in theoretical and practical aspects. Theoretically, this study suggested one of the possible generative mechanisms of cyberbalkanization, which is mutual ignoring, but it is conditioned by the situation of a low theoretical barrier in communication. Also, our finding supplements the existing body of knowledge about the genesis of cyberbalkanization which mostly focuses on individual behaviors such as selective exposure or motivated reasoning. In a network perspective, we advocate theorists should holistically consider both individual behaviors and the interactions between individuals.

Practically speaking, while we have shown that cyberbalkanization is one precedent factor for opinion polarization, we propose a strategy for minimizing cyberbalkanization by encouraging a higher chance of edge formation between different users, e.g. random suggestion of sharable contents generated from other communities to encourage post sharing. The algorithmic suggestion of sharable contents imposed on the user's timeline based on similarities in social network characteristics might encourage mutual ignoring and result in cyberbalkanization.

In conclusion, the current study demonstrated the use of triangularization approach of combining agent-based model and network analysis, which suggested that mutual ignoring might be a generative mechanism of cyberbalkanization.

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Table 1. Communities identified from the Hong Kong Facebook Pages sharing network

Name	Top 3 pages (by betweenness)	number of pages
Autonomists	聚言時報 Polymer 有種美德叫有種 by 陳到 PassionTimes 熱血時報	332
Pro-Beijing / Blue Ribbon #1	時聞香港 向香港警察致敬 光復香港	37
Mainstream Pro-activists #1	蘋果日報 香港獨立媒體網 Keyboard Frontline 鍵盤戰線	570
Conservationists	集雜誌 Zine 新新青年互助委員會 本土研究社 Liber Research Community	68
Radical media	寰雨膠事錄 PlasticNews.wf 方健儀 Akina Fong 「多謝支持 後會有期」 輔仁媒體	31

Movie and entertainment	Edko Films Ltd. 安樂影片 Warner Bros. (HK) 電影與娛樂盛事 Movie & Event Marketing	31
Pro-Beijing / Blue Ribbon #2	佔中不代表我 我支持劉 Sir 仗義執言 香港培青社	56
trivia	我係香港人 I am a Hongkonger 香港地笑話 昔日香港	32
Teen Magazine	東 TOUCH U Magazine 3c Music	89
Mainstream Pro- activists #2	健吾 100 毛 社漫三號機	384

Table 2. Triad census of the Hong Kong Facebook sharing network

nomenclature	configuration	Amount	Percentage	Expected percentage generated by Barabási -Albert model (linear preferential attachment)
003	1 - 003	4,317,322,83 9	97.69	99.4
012	2 - 012	90,900,963	2.06	0.59
102	3 - 102	7,669,455	0.17	0
021D	4 - 021D	1,012,996	0.02	0
021U	5 - 021U	1,356,002	0.03	<0.01
012C	6 - 021C	587,069	0.01	<0.01
111D	7 - 111D	210,647	< 0.01	0
111U	8 - 111U	198,967	< 0.01	0
030T	9 - 030T	136,397	< 0.01	0

030C	10 - 030C	2,312	< 0.01	0
201	11 - 201	18,914	< 0.01	0
120D	12 - 120D	23,118	< 0.01	0
120U	13 - 120U	24,535	< 0.01	0
120C	14 - 120C	9,152	< 0.01	0
210	15 - 210	9,447	< 0.01	0
300	16 - 300	1,718	< 0.01	0

Table 3. Mean modularity and number of edges in simulated networks generated from various sets of experimental conditions

P_{MaxRT}	Preferential attachment only - No mutual ignoring	mutual ignoring - mutual choice	mutual ignore - random choice	Mutual ignoring - sync
1/1000	0.013 / 182000	0.013 / 184934	0.013 / 180418	0.025* / 104357 *
1/10000	0.085 / 23279	0.085 / 23721	0.086 / 23515	0.085 / 23256
1/100000	0.359 / 2400	0.345 / 2504	0.360 / 2399	0.357 / 2430

Data are displayed as mean modularity / mean number of edges

* $p < 0.001$, One way anova

Figure 1: The configuration of “mutual ignoring” (102) triad

Figure 2: The log-log plot of degree distribution in the Hong Kong Facebook Pages sharing network