Investigating Preferential Attachment Behavior over the Evolution of Disaster Response Networks

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Abstract
This study aims to understand the mechanisms of disaster response network evolution by quantitatively examining the actors’ attachment behaviors in a real disaster collaboration networks. We aim to do this by identifying the characteristic of existing actors and its impact in forming new connection over time. To quantify actors’ attachment logics (i.e., preferential attachment), different options of attachments (between and among new and existing actors) are considered. The result indicates the existence of cumulative advantage for actors involved in a response network to a disaster. We argue that by understanding the mechanisms of network evolution, we can predict more precisely how the behavior of actors and network structure evolve over time. This can assist researchers, decision makers or practitioners to manage and support collaboration of actors in their systems for reaching their organizational goals. The overall findings of this study can contribute further to the development of network organizational theory, organizational learning theory and self-organizations in different contexts especially disaster and emergency response management.

1. Introduction

Complex systems surround our human life by a wide range of natural networks (e.g., human brain, proteins, and ant colonies), socio-economical networks (e.g., world trade union, corporations’ organizational structure) and socio-technical networks (e.g., the World Wide Web, the Internet, and Facebook) [1]. In order to examine the flow of information (or any resources) across the networks, interaction patterns among actors and networks or systems’ performance, there is a need to study the networks’ structure, both local structure of the actors and global structure of the whole network.

In order to understand social and organizational dynamics, evolutionary theory has been used widely by many social scientists and organizational scholars. Evolutionary theory was originally developed to explain the emergence and transformation of biological phenomena in the natural world [2].

Powell et al., [3] and Glückler [4] summarized and identified cumulative advantage as one of the attachment logics to explain the structure and dynamics of networks during the evolution of networks over time. Cumulative advantage or preferential attachment shows how actors’ positions in the pre-existing network structure affect the formation of new ties [27-28, 30]. It can be observed in dynamic networks that actors in the network adapt themselves with the changes in new network structure looking for new alternative partners.

Even though the results by Barabasi and others on the process of preferential attachment (e.g. [5]) are well known in the field, either new, additional, complementing or fine-grained insights on the topic are key in improving our ability to control, manage or orchestrate (cf. [6]) complex (human) systems.

Importance of understanding the behavior and position of nodes (actors) in analyzing the network has been instrumental in the growing interest for studying complex networks especially from the evolutionary perspective, with consideration given not only in an specific point in time (static) but also during the evolution (dynamic) of the network. Understanding of evolutionary behaviors of complex networks can assist in predicting the network structure but also nodes status in future. One of the important outputs of such studies is to identify influential nodes in a network, which facilitates network expansion. This has implication for decision makers and managements in supporting collaboration in line with networks expansion. For instance, investing on special strategic position of a person (actor) in his/her social network which attract or influence his/her partners during the expansion of network for the case of viral marketing.

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can help a company to sell their products faster through that person.

By studying dynamic structural properties and patterns of evolution of complex networks, we aim to examine: (i) the flow and spread of information (or any resources) through a network; (ii) the local structure and behavior of nodes which impact on the global structure of the network during its evolution (expansion); and (iii) influential nodes to make a network more resilient. This study aim to find the behavioral attachment patterns by identifying specific characteristic of existing actors and its influence in attracting new actors or cause new actors attach to them. To reach the research objectives, this study attempts to provide answers for the following research questions:

- How do actors’ preferential attachment logic influence on their attachment behavior during the evolution of a complex disaster response network?
- How does network structure influence the preferential attachment behavior of actors?

To address these questions, we review the literature on theories of network evolution and preferential attachment (cumulative advantage) during the evolution of complex networks in Section 2. Then, data sources and collection methods are described in Section 3 in addition to the measures that are used. Section 4 provides the results of our analysis and finally the paper ends with conclusions and a discussion of the findings highlighting the implications and limitations of this study.

2. Understanding the evolutionary dynamics of complex networks

Complex systems surround our human life by a wide range of networks in nature and society (e.g., ant colony, cells interaction, World Wide Web, Facebook). Node in these networks can be a cell, a person, a computer, an organisation, a country or even a group of any of them whereas ties can take the form of friendship, communication, collaboration, alliance, or trade, to name only a few [7]. For instance, a friendship network consists of persons (nodes), which any pair of them are linked if they are friends. Or, World Wide Web can be regarded as a complex network (with huge amounts of nodes which are Web pages) that are connected to each other if there is a hyperlink between them.

Many research problems within a wide range of disciplines can be framed within a network perspective [7, 8]. This has led to the development of graph theory in mathematics and computer science, social network analysis in sociology, and the analysis of complex networks in statistical physics and biology [9].

2.1. Network evolution theories

Network structure dedicates how network is organized and viewed, which provides an understanding of how actors in a network are connected to each other. It is one of the most important attributes of a network. Study of network structure relates to uncovering the global structural patterns which emerges from the ways in which actors (as nodes in a network) behave at a local level [9]. Several studies were aimed at improving our understanding of human interaction patterns [10-12]; On the other hand, others focused on the spread of information and infectious diseases [13], and the effect of network on actors’ and organisations’ performance [14-17].

Evolution can be considered from the viewpoint of individual nodes, their individual paths of development, and the mutual influence they have on one another [18]. Both evolutionary approach and network approach emphasize on flows of resources as it shapes the formation of ties (micro level) and the emergence of network structure (macro level) [19].

The essential starting point for any theory of network evolution is the question of ‘how do structural dimensions of a network affect the future interactions among actors?’ [20]. In other words, how structure of a network at time t affects formation of new ties at t+1? Thus, a theory of network evolution, looks at the impact that network structure imposes on the formation of new ties and conversely, at the changes that every new tie produces in the existing structure. It is important to note that the unit of analysis is always dyadic tie formation, whereas the object of knowledge is network structure [4].

In order to understand the mutual effect among dynamic network structure and new ties formation, we review several empirical studies on the theory of network evolution and tie formation in social science studies.

Evolutionary theory was originally developed to explain the emergence and transformation of biological phenomena in the natural world [2]. Many social scientists and organizational scholars used evolutionary theory to understand social and organizational dynamics e.g. [21-23]. Evolutionary theory has a number of advantages over more traditional approaches to the study of networks [18]. For instance, full understanding of the evolution of organizational communities requires insight into both organizations and their networks.

Evolutionary theory highlights how networks (e.g., organizations, communication networks) change in
terms of birth, growth, transformation, decline, and demise rather than taking a static perspective [18, 24]. Therefore, the application of evolutionary theories significantly contributes to understanding the temporal dynamics of networks’ structural change [19].

The selection of a tie depends on both the decisions of the interconnected actors involved and also external selective environment [4]. This implies a dual conceptualization of selection mechanisms that selection may be a function of: (i) external changes on the degree of adaptation of relationships; and (ii) internal motivations in selecting and changing linkage by both actors involved in a relationship [4]. For instance, in a co-authorship network linkage may happen because of external issues (e.g., student-supervisor, researcher-sponsor) or internal issues (e.g., coauthor is a prominent scholar).

Actors in a network (e.g., organizations) invest resources (e.g., people, time, money, and expertise) to create relationships and linkages that provide other resources [18]. For instance, they expend economic or human capital in order to build their social capital (i.e., their connections to other actors in the network) from which they hope to profit [15]. Therefore, linkages can be classified as an investment that is either internal (establishing, maintaining and managing costs) or external (negative network externalities) [18].

2.2. Preferential attachment

Using multiple novel methods, Powell et al., [3] demonstrate that during the expansion (evolution) of networks how logics of attachment shift over time. They identified cumulative advantage as one of the important logics of attachment to explain the structure and dynamics of inter-organizational collaboration.

Cumulative advantage is a process in which the highly-connected nodes receive more new ties in following stage [3]. The cumulative advantage process is based on “the rich get richer” principle which was originally proposed by Yule [25] (known as Yule distribution) or “the Matthew effect” which was originally used by Merton [26]. It was also elaborated by other researchers such as Price [27] who used the same terminology (“cumulative advantage”). All these processes are based on a general mechanism through which a relatively favorable position becomes a resource to generate further gains [28]. “Preferential attachment” terminology originally used by bringing that concept into network science (social network analysis).

It has been shown that actors’ positions in the pre-existing network structure affect the formation of new ties [29]. One of the main findings of the literature examining network embeddedness is that actors that are highly embedded in a network (i.e., actors with many existing social ties, such as alliances with other firms that provide them with a central position in the network) are more likely to form additional alliances because of their ability to gather information about a wider set of potential collaborations [30], and because of their high status resulting from their central position in the network structure [31]. Although well-positioned actors gain cumulative advantage in their connectedness but there is a probability of unconnectedness for peripheral actors in the network [32]. It has also been shown that many not only actors’ existing connections led to the future formation of their links but also other factors such the actors brokering role in the network [33].

3. Methodology and data

To quantitatively analyze networks, they should be transferred in matrix formats to be able to apply mathematical analysis and metrics. Social network analysis, as a kind of mathematical analysis method, views relationships in terms of network theory consisting of nodes and ties. Therefore, the social network analysis metrics (e.g., individual centrality measures, network centralizations, network density, and network clustering coefficient) can be used in order to quantify actors (actors) and networks properties and structural attributes.

3.1. Methodology

Social network analysis (SNA) is the mapping and measuring of relationships and flows between nodes of a social network. SNA provides both a visual and a mathematical analysis of human-influenced relationships. The social environment can be expressed as patterns or regularities in relationships among interacting units [7]. Each social network can be represented as a graph made of nodes (e.g., actors, organizations, information) tied by one or more specific types of relations, such as financial exchange, friends, trade, and Web links. A link between any two nodes exists, if a relationship between those nodes exists.

Measures of SNA, such as centrality, have the potential to unfold existing informal network patterns and behavior that are not noticed before [34]. A method used to understand networks and their participants is to evaluate the location of actors in the network. Measuring the network location is about determining the centrality of an individual. These measures help determine the importance of a node in the network. To quantify the importance of an
individual in a social network, various centrality measures have been proposed over the years [35].

Recently, the analysis of networks and particularly the dynamics in the evolution of large networks has become of greater interest to more authors. Given the increasing evidence that networks obey unexpected scaling laws (Albert, Jeong, & Barabási, 1999; Barabási & Albert, 1999) that can be interpreted as signatures of deviation from randomness (Jeong, Néda, & Barabási, 2003), there have been efforts resulting in a class of models that view networks as evolving dynamical systems, rather than as static. These approaches look for universalities in the dynamics governing network evolution (Jeong et al., 2003).

### 3.2. Data

During emergency and disaster situations actors from different agencies cooperate to properly respond to the incident collectively. Inevitably, participants need to interact, communicate and cooperate with each other through the use of sharing information and experience, reporting and briefings, requesting resources and so on. Therefore, coordination network shapes, including agencies or participants from different organizations (agencies) as actors and their communication (interaction), represent the links or ties among actors in order to respond to the emergency.

Coordinating activities or tasks in a complex system during a disaster for effective response is one of the most important issues to protect human, natural lives as well as from infrastructure damage. Therefore, a deep understanding of inter-organizational response network structure and the process of locating information flow and exchange is necessary in optimizing the response networks. This helps emergency managers and policy makers in making better informed decisions.

In 2009, the state of Victoria was burnt severely during February 2009. Although several agencies warned of the continuing fire threat and the forecast extreme conditions for 6 and 7 February but “Conditions prevailing in the State on 7 February were unparalleled in Australia’s history” [36].

The 2009 Victorian Bushfires Royal Commission was established on 16 February 2009 to investigate the causes and responses to the bushfires which swept through parts of Victoria in late January and February 2009. The data used in this research comes from content analysis by reviewing Victorian Bushfires Royal Commission situation reports after the February 7, 2009 (Black Saturday). Royal commission situation reports were made available to the public and are available at http://www.royalcommission.vic.gov.au.

The Kilmore East fire (which was actually a group of separate fires) started on February 7. The Kilmore East fire that ignited on 7 February 2009 was extraordinary and unprecedented. It was the fire with the most severe damages and fatalities. In all Kilmore East fires, “119 people died and 1,242 homes were destroyed. The combined area burnt by the Murrindindi and Kilmore East fires, which later merged, was 168,542 hectares. The Kilmore East fire alone burnt 125,383 hectares” [37].

During the data collection process, we first reviewed the brief reports on the Kilmore East fire. Then, identifying key participants mainly in the Incident Management Teams (IMTs) such as Incident Controller (IC) and its deputy (DIC), Planning Officers (PO), etc. involved in the emergency response network, we look for the actors statements in the Royal commission dataset.

From the result of the content analyses of the 2009 Kilmore East fire, we identified the main key actors involved in the response, and support management mainly in incident management team. Then, the statements of each key actor were extracted again searching the Royal commission dataset. Applying content analyses on the key players’ statements, their interactions were documented. Finally, 104 distinct actors and 286 interactions among them were extracted.

### 4. Analysis and results

#### 4.1. Investigating logics of attachment of actors during network evolution

During evolution of a collaboration network, attachments (new links) may happen: (1) between new actors (added in the following period) and existing actors; (2) among new actors; (3) among existing actors who were not connected before; and (4) among existing actors who already had at least one connection.

Table 1 shows the growth of Kilmore fire disaster collaboration network by showing the cumulative number of actors and links among them during network evolution between T1 and T4.

Table 1 for each year indicates the growth of sum of links that is slightly more than growth of the number of links (considering cumulative numbers).
Table 1. Kilmore fire actors and their collaborations (links) statistics

<table>
<thead>
<tr>
<th>Time</th>
<th># of actors</th>
<th># of Links</th>
<th>Sum of Links</th>
<th>Avg. Link/Au</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>43</td>
<td>46</td>
<td>73</td>
<td>1.07</td>
</tr>
<tr>
<td>T2</td>
<td>35</td>
<td>47</td>
<td>80</td>
<td>1.31</td>
</tr>
<tr>
<td>T3</td>
<td>41</td>
<td>42</td>
<td>60</td>
<td>1.02</td>
</tr>
<tr>
<td>T4</td>
<td>40</td>
<td>46</td>
<td>73</td>
<td>1.15</td>
</tr>
</tbody>
</table>

Table 2 shows the number of actors and new actors per period (between T1 and T4) in addition to the number (and percentage) of new actors who attached to an existing (old) actor. It also shows number of existing actors (from previous period) who have attached to at least: (i) a new actor or (ii) another existing actor or (iii) any actor (no matter a new or old actor).

The results indicates that the number of new actors who attached to existing actors is much higher than the percentage (and number) of new actors who attached to another new actor. Almost all the new actors in all periods have at least one connection with existing actors.

Studying attachment behavior of existing actors (from previous period), as shown in right side of Table 2, indicate that almost half of the existing actors connect to any other actor during T1 but this rate decreases as network grows over time. Out of those attachments of existing actors, almost the same amount attached to other existing actors but a few of them linked to the new actors. For instance, only 47% of existing actors in T1 have a new link during T2 and just 19% (which is less than half of the existing actors with new link at T2, 47% of all existing actors) had a connection with the new actors but all of them had at least a new link with other old actors.
Table 2. Kilmore fire actors (nodes) attachment statistics per period of time

<table>
<thead>
<tr>
<th>Time</th>
<th># of actors</th>
<th># new actors</th>
<th># NEW actor attached to at least</th>
<th># OLD actors attached to at least</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>a NEW actor</td>
<td>an OLD actor</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T1</td>
<td>43</td>
<td>8 (19%)</td>
<td>8 (19%)</td>
<td>20 (47%)</td>
</tr>
<tr>
<td>T1-T2</td>
<td>58</td>
<td>15</td>
<td>2 (13%)</td>
<td>15 (100%)</td>
</tr>
<tr>
<td>T1-T3</td>
<td>76</td>
<td>18</td>
<td>4 (22%)</td>
<td>17 (94%)</td>
</tr>
<tr>
<td>T1-T4</td>
<td>98</td>
<td>22</td>
<td>0</td>
<td>22 (100%)</td>
</tr>
</tbody>
</table>

Table 3. Kilmore fire actors’ collaborations’ attachment statistics per period of time

<table>
<thead>
<tr>
<th>Year</th>
<th># of Coll.</th>
<th># of new Coll.</th>
<th># of collaborations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>among NEW actors</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T1</td>
<td>73</td>
<td>31 (42%)</td>
<td>31 (42%)</td>
</tr>
<tr>
<td>T1-T2</td>
<td>153</td>
<td>80</td>
<td>1 (1%)</td>
</tr>
<tr>
<td>T1-T3</td>
<td>213</td>
<td>60</td>
<td>2 (3%)</td>
</tr>
<tr>
<td>T1-T4</td>
<td>286</td>
<td>73</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3 above shows the statistics about number of collaborations (sum of links), and the number of new collaborations per period followed by number of new links: (i) among new actors; (ii) between new actors and existing actors; (iii) among existing actors who had no collaboration (link) before; and (iv) among existing already connected actors.

As the results indicate, most of the new collaborations occur between new and old (existing) actors. For instance, 40% of the new actors had collaboration to an existing (old) actor during T1-T2 while only 1% the new actors had collaborations with other new actors. Considering existing actor at T1-T2, only 26% of them had collaboration with other existing actors, 18% with already connected actor plus 8% as new links with the existing actors. The results also indicate that disconnected existing actors attached to each other more than existing connected actors (redundant collaborations) did.

The higher rate of attachment among existing actors compare to the attachment rate between new and existing actors, expresses that embedding process (attachment based on the ties strength among actors) is playing an important role in the attachment behavior of actors during the disaster collaboration network evolution. It means that the existing actors who are intensively connected intend to have new links together in future.

Although new actors’ attachment frequency to existing actor is very high, but the frequency of attachment between new and existing actors reveal that the actors intend to diversify their links with different actors. Therefore, this indicates the existence of multi-connectivity process in actors’ attachment behavior during the evolution of the disaster collaboration network but not as high as the embedding process.

Moreover, focusing on the links rather than actors, Table 4 shows that the highest number of attachments (new links) per duration is between the new actors and existing actors. The new links among old actors who were connected prior to that duration are ranked next followed by the number of attachments among old actors who was not connected before as third rank.

Therefore, the embedding process of attachment can be seen (but not strongly) among existing actors who make new connection with the existing one who they already know as trust is important in disaster conditions.

In order to investigate actors preferences’ attachment based on their positional characteristics in the network, first major centrality measures (i.e., degree, closeness and betweenness) of each existing actor at time t (e.g., T1) are calculated. Also, the frequency of new links (attachments) to the existing actors at time t+1 (e.g., T4) is measured. Using Spearman correlation rank test, we test the association between existing actors’ centrality measures (i.e.,
degree, closeness and betweenness) and the numbers of attached actors to them in the following year between T1 and T4.

As Table 4 indicates three major centrality measures (i.e., degree, closeness and betweenness) of actors positively correlated to the numbers of new actors attached to them. The result of the correlation test supports the classical preferential attachment rule for the disaster collaboration network. It also suggests that new actors prefer to attach to the actors with high number of connections (high degree centrality). This also asserts that the new actors prefer to attach to the actors who are having brokerage role in the collaboration network (high betweenness centrality).

Table 4. Spearman correlation coefficients between actors’ centrality measures and their attachment frequency in each stage

<table>
<thead>
<tr>
<th>Centrality Measures</th>
<th>number of new added actors (in the next stage)</th>
<th>T1</th>
<th>T1-T2</th>
<th>T1-T3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree Centrality</td>
<td>P</td>
<td>.622 **</td>
<td>.531 **</td>
<td>.384 **</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>43</td>
<td>58</td>
<td>76</td>
</tr>
<tr>
<td>Closeness Centrality</td>
<td>P</td>
<td>.146</td>
<td>.375 *</td>
<td>.335 *</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>43</td>
<td>58</td>
<td>76</td>
</tr>
<tr>
<td>Betweenness Centrality</td>
<td>P</td>
<td>.515 **</td>
<td>.577 **</td>
<td>.440 **</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>43</td>
<td>58</td>
<td>76</td>
</tr>
</tbody>
</table>

As the result shows the correlation coefficient between betweenness centrality of actors and their attachment frequency (in the following period) is always significant and much higher than degree and closeness centrality measures (except the first period that degree’s coefficient is higher) during all periods the collaboration network evolves. This means that actors with high betweenness centrality measure attract more actors than other actors who have many co-actors during the evolution of the disaster collaboration network. In summary, more actors prefer to attach to the existing actors who are controlling the flow of information (communication) by having broker (gatekeeper) role in the collaboration network which connect otherwise disconnected actors or group of actors.

Furthermore, looking at each centrality measures’ correlation coefficients changes over time, the correlation coefficients between number of new connected actors and degree centrality is decreasing over time. Therefore, as collaboration network grow, betweenness centrality becomes more and more important in terms of attachments and the actors with high betweenness centrality gain more power and influence by attracting new actors. Therefore, the preferential attachment process can be seen as a good attractor of actors’ attachment during the evolution of the disaster collaboration network [33].

5. Conclusion and discussion

This study synthesized different theories and approaches of the evolution of complex networks from various fields with an aim to explore the evolutionary processes of networks structure for examining the evolutionary dynamics of networks. The study addresses actors’ preferential attachment logics (i.e., cumulative advantage) over the evolution of networks.

This study suggests a way to improve the techniques for identifying the nodes with strategic position in a network can assist in improving collaboration within the network in different fields. The findings can have implications in variety of fields to facilitate information or resources flow such as in disaster management to facilitate the dissemination of information and resources, or in political science to invest on the individual who can influence other individuals and communities faster and more effective to spread the information the political parties need in order to reach their goal, or in market research to invest on the actors who can attract more customers.

This study contribute to the emergency management field as: (i) it is one of the first studies (in addition to [38]) on analyzing the evolution of disaster collaboration response networks over time; (ii) using data collected from disaster networks provide a perfect setting for studying the process of preferential attachment in a self-organizing human system; when a disaster occurs, people will want to behave in a way optimal to them and the ones that they feel responsible (instead of letting e.g. “politics to affect their decisions”) as the coordination for disasters are not actually followed the pre-made plans [38].

6. References


