The Evolution of Community Structure in a Coauthorship Network

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ABSTRACT

Mechanisms such as triadic closure and preferential attachment drive the evolution of social networks. Many models use these mechanisms to predict future links, and they generate realistic networks with scale-free degree distributions. These social networks also have community structure, or sets of vertices which are more connected to each other than the rest of the network. To study the evolution of research groups of scientists in a coauthorship network, we use a *time-heterarchy* representation to extend the mechanisms driving the evolution of the network to the level of this community structure. Specifically, we examine changes in the structure of groups in terms of mechanisms analogous to triadic closure and preferential attachment, and as a result, we find that the network evolves in the same way at the group-level and the individual-level. In addition, we find that interactions at the group-level might affect interactions at the individual-level in that members of a single group are more likely to strengthen their relationships than members of separate groups.

Keywords: Social Networks, Coauthorship Networks, Community Structure, Network Evolution, Preferential Attachment, Triadic Closure.

1. INTRODUCTION

With the aim of quantifying the evolution of relationships over time, a long history of studies have proposed and tested mechanisms which drive the evolution of networks of 'actors' connected by 'ties'[1]. In general, these studies either build models of network formation which yield networks with similar topology to real-world networks, or they empirically test mechanisms which drive the changes in the network.

Most of the models and studies on the evolution of networks either use or test the mechanism of preferential attachment [2, 3, 4, 5]. This mechanism suggests that well-connected or high-degree vertices are more likely to obtain new ties than less well-connected vertices. This trend explains the scale-free or power-law distribution of degree in most real world networks. Intuitively, this means that a small number of vertices in the network will have many of the connections, and the remaining majority will have fewer connections.

In addition to preferential attachment, triadic closure drives the clustering of vertices in a network [6]. This mechanism assumes that a third edge is likely to form between two actors if they share ties with a common vertex. In other words, triangles in the network are likely to close. Link prediction models sometimes use this information to take a set of vertices and edges at one time period, and predict the set of edges at the next time period [7, 8].

Mostly disjoint from the study of the evolution of networks, other work has focused on the community structure of a single time period [9, 10, 11, 12, 13]. In general, this work attempts to identify subsets of vertices which are more connected to each other than to the rest of the network. To complete this task, some algorithms find and remove edges which are likely to lie between groups [9, 11], others use a measure of similarity between vertices to place each in a category (hierarchical clustering)[1], and the newer CFinder algorithm uses clique-rolling [13]. The output groups of these (general purpose) algorithms vary in their exact constituents, but in general the algorithms produce sets of well-connected vertices.

In this study, we bring together the network evolution and community structure literature to understand the evolution of groups. We focus on the evolution of a coauthorship network, or a set of vertices representing researchers connected by edges representing coauthored papers. Within this network, we use a community structure algorithm (developed specifically for coauthorship networks [14]) to identify collaboration between researchers, and observe evolution of this community structure over time. Similar studies used the CFinder algorithm to test the stability of groups over time, and extended preferential attachment to the group level [15, 16]. Using our algorithm [14], we reproduce their results by confirming group preferential attachment as a mechanism behind network evolution, and we extend triadic closure and relationship strengthening to the group-level. In addition, we view the effects of individual interactions on the formation of groups as well as the effects of group membership on the formation of new relationships between individuals. In general, we are interested in the relationship between individual-level and group-level mechanisms, and the extent to which we can reduce explanations at one level to explanations at the other level. This relationship between groups and individuals demonstates the functional role of community structure within the network.

In the next section, we give a brief overview of the methods we employed to examine the evolution of the network. In Section 3, we reproduce results which validate mechanisms which drive evolution at the individual-level. Next, in Section 4, we view the effects of community structure on individual-level mechanisms. As the main focus of the paper, in Section 5 we quantify the evolution of community structure in terms of group-level mechanisms which are analogous to the individual-level mechanisms of Section 3.

2. METHODS AND DATA

Community-structure Algorithm

We differ in our methods from previous studies [15, 16] which have viewed the relationship between the evolution and the community structure of a general network in that we focus specifically on a *coauthorship* network and the effects of its structure on the organization of research. While the algorithms of other studies detect groups primarily through the assumption that a group consists of a well-connected subset of the network, they typically make no assumption about the structure specific to the type of network they are studying. In contrast, we attempt to identify groups by focusing on the way in which scientists collaborate. Instead of treating a coauthorship network as equivalent to any other social network, we make assumptions regarding the structure of individual groups. We assume that key scientists, or Principle Investigators (PIs), arise in the network, and collaborators organize themselves around these leading figures. Using these assumptions, we construct an algorithm which simulates this process on a given network. For a detailed description of the algorithm, see [14].

Using an alternative CFinder algorithm, a similar study performed the task of analyzing the stability of groups and extending preferential attachment to the group-level[15, 16]. In Section 5 we are able to reproduce their results through a slightly different method. While similar conclusions are drawn from the two community structure algorithms, their methods and assumptions differ. Most noteably, the algorithm we use is specifically crafted for the identification of groups of researchers in a coauthorship network, and our primary goal is restricted to analysis of research networks.

Due to the common assumption that more links exist between members of a single community than between members of different communities, we speculate that many community structure algorithms could reproduce the group-evolution results. The choice of algorithm only determines the methods by which the various mechanisms are tested, and also gives a slightly different flavor to the implications of the results. For example, the group-level preferential attachment identified by CFinder implies that large groups of well-connected *members* of an arbitrary network are likely to collaborate with other large groups. Contrastingly, the same result produced by our algorithm implies that *researchers* collaborating with PIs in large groups are likely to form new groups around other PIs with other researchers who are in large groups. In this example, our algorithm narrows the implications of group-level preferential attachment to a statement about the formation of groups around PIs. This shows that by adding extra assumptions to our algorithm (and extra structure to the communities), we are able to draw conclusions specific to the structure of research.

Network Data

For this paper, we use a unique dataset [17] containing all papers published under the categories of Physics and Applied Physics/Condensed Matter/Material Science between 1981 and 2003 with at least one author whose address is in Mexico. We choose fields related to physics following a number of studies on these fields in other regions around the world [3, 18, 19]. Also, in Mexico, areas related to physics have a long tradition of publishing in international peer reviewed journals, indexed by ISI.

From the database, we use information regarding article names, authors, addresses, years of publication, references, and forward citations. Most pertinent to the results presented in this paper, we retrieve article titles and authors to construct a coauthorship network. Specifically, for every author, a vertex is added to the network, and for every paper, a connection is added from every coauthor to every other coauthor. Connections between two authors have weight equal to the number of papers they have coauthored together.

Intervals

As a method for viewing the evolution of the network over time, we split the data into 5 year intervals from year x to $x + 4$, and we construct a separate coauthorship network for each of these intervals. Unless otherwise specified in the following sections, we consider *adjacent intervals* to be intervals $I_1 = x$ to $x+4$ and $I_2 = x + 1$ to $x + 5$ where $1981 \leq x \leq 1999$. By showing the addition and removal of new edges one year at a time, these overlapping time periods demonstrate gradual changes in collaboration.

3. INDIVIDUAL EVOLUTION

Before considering the evolution of the community structure of the network, we briefly present results related individual-level mechanisms such as preferential attachment and triadic closure. In addition, we extend previous results regarding changes in individual relationships to account for edge weight. The majority of these individual-level results only give context to the group-level results, and therefore we will only give a brief overview.

Preferential Attachment

We find that the coauthorship network at each 5 year time interval has a scale-free degree distribution. As this distribution usually follows from preferential attachment, we ensure that this is the case for our network. Following previous studies [2, 3], we test preferential attachment for new authors attaching to existing authors. Viewing adjacent intervals I_1 and I_2, we let new authors be the set of authors in I_2 not in I_1 and existing authors be the set of authors in both I_1 and I_2. Next, we consider the probability that a new author n attaches to an existing author e who has degree k in interval I_1. Using this method, we find that the probability of new collaboration with an existing author increases with the existing author's degree. Reproducing the results of Barabási *et al* [2], the probability of attachment to an author of degree k

follows a function of the form $Pr(Attach_k)\tilde{}k^b$. Across all adjacent time intervals from 1981 to 2003, the value of b ranges from 0.579 to 1.288 with an average value of .850 (Barabási reached similar values of .8 and .75 for other networks). As expected, this implies that new authors entering the network tend to choose well-connected authors for collaboration.

Also following Barabási *et al*, we find that existing authors are more likely to begin collaborating with well-connected existing authors. To measure this, we take the set of authors who stay in the network through intervals I_1 and I_2. Then, the probability of attachment between authors of degree k_1 in I_1 and authors of degree k_2 in I_1 is the number of connections which form between them in I_2 divided by the possible number of new connections. As expected, this probability increases with the degrees of each author. For example, two authors with degree 1 have a probability of $1e-5$ of attachment, whereas an author of degree 38 has a probability .11 of attaching to an author of degree 18. In the next section, we observe triadic closure, which might influence this trend.

Closure

To more thoroughly examine the network's evolution at an individual level, we test triadic closure and the changes of individual relationships over time. The results of this analysis reproduce and extend the results of Newman in Ref. [3]. Specifically, we test triadic closure similarly to the way in which Newman examines clustering. In addition, we extend his notion of probabilities of coauthorship based on past collaboration to account for changes in weight.

We test triadic closure, or the formation of a new edge between two authors who already share a common collaborator [6], by comparing the number of length-2 paths between two unlinked authors with the probability that they form a direct connection in the future. To compare past occurences with future occurences, we consider each 5 year interval from year y to $y+4$ in relation to the interval $y+5$ to $y+9$ across all intervals from 1981 to 2003. Using this method, the probability of future collaboration increases with the number open triangles between two authors (as shown in Figure 1).

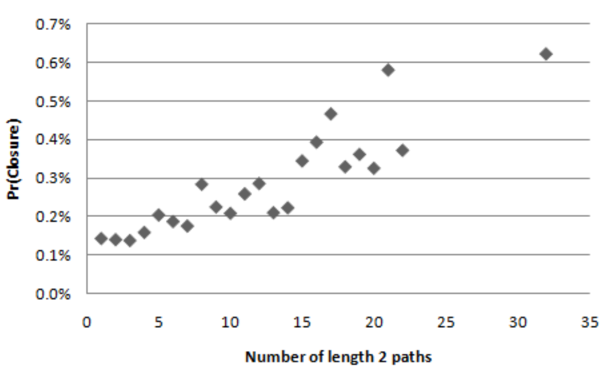

Figure 1: The number of closures between two authors increases with the number oflength 2 paths.

Strengthening

Using the same type of interval comparison as in the triadic closure measurements, the probability of a future edge increases with the weight of a current edge. Extending this result, we also find that the average weight of the future edge increases with the weight of the current edge. In addition, the trend shows that higher weights tend to decrease in the next time period. Specifically, only links of weight 2 have an average weight increase, whereas links of weight 6 decrease on average by nearly 2 papers.

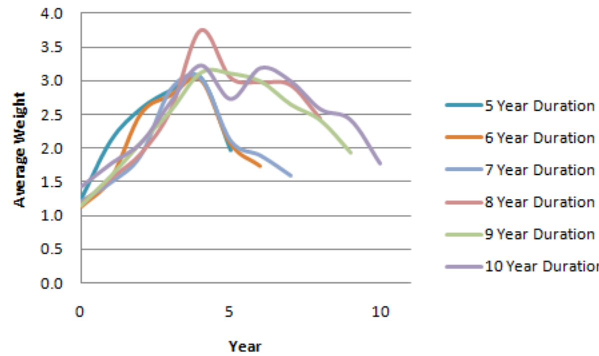

Figure 2: Time series for individual link weights across adjacent intervals. There is a separate plot for each relationship duration, or the number of adjacent intervals through which an edge perseveres.

Since low weight (weight 1 and 2) edges tend to increase, and higher weight edges tend to decrease, it is reasonable to assume that individual link weights start low, increase to a peak, and then decrease. Figure 2 shows evidence for this assumption by charting average weights over time. The chart shows that longer duration relationships strengthen for a period, and then decay back to nothing. Contrastingly, relationships which last less than the 5 year timespan of a single interval tend to have constant weight. These observations of weight trends might help in link prediction models similar to those in Ref. [7, 8].

4. INDIVIDUAL-GROUP EVOLUTION

As an extension of the results given in the previous section, we consider the way in which groups influence triadic closure and relationship strengthening. In both cases, the probability of future links is higher between members of a common group than between members of different groups.

For triadic closure, we perform the procedure described in the previous section, except that we consider triangles whose open edge lies between members of the same group separatetely from triangles whose open edge lies between members of different groups. Unsurprisingly, we find that triangles are more likely to close between group members. In most cases, triangles within groups are approximately 10 times as likely to close as triangles outside groups. These results suggest that community structure might provide a means by which to make better predictions about future edges between individuals.

In contrast to triadic closure, the probability of a future edge between two authors given the weight of a current edge only differs inside and outside of groups for low edge weights. As shown in Table 1, as edge weight increases, the differences in probabilities of future in-group edges and future between-group edges become less noticeable. These differences are consistent with the relationship time series of the previous section. The discrepency between low weight probabilities suggests that edges within groups are at a different point in the time series than edges between

Current Weight	Pr(In-Group)	Pr(Out-Group)
0	0.060	0.001
1	0.519	0.398
2	0.638	0.539
3	0.719	0.745
4	0.822	0.750
5	0.792	0.818
6	1.000	N/A
7	0.882	1.000
8	1.000	1.000

Table 1: The probability of a future edge between authors a_1 and a_2 given the weight of current edge between a_1 and a_2. We separately consider cases where a_1 and a_2 are in the same and different groups.

groups. More specifically, since probabilities of future edges inside groups are higher, this suggests that edges between members of a common group tend to be at the start of the time series, while outside-group edges tend to be at the end of the time series. Therefore, weak relationships between groups tend to be decaying relationships, while weak relationships within groups tend to be growing relationships. Also, since stronger relationships only occur at the peak of the time series, they can only decay. As a result of this single option, there is less discrepency between strong relationships within groups and outside groups.

5. GROUP EVOLUTION

Following our characterization of the network's evolution at the individual-level through accepted mechanisms of preferential attachment and triadic closure, we now attempt to extend these notions to the level of groups. Because the situation for groups is not entirely similar to the situation for individuals, it is necessary to develop a slightly different method for observing these characteristics. More specifically, in contrast to the constant stability of a single individual, a group tends to break apart over time. Therefore, in order to observe an individual mechanism at the group-level, we must either (1) restrict the analysis to stable groups, or (2) make a slight alteration to render the concept useful when applied to unstable groups. The algorithm of Palla *et al* produces overlapping groups, and they utilized this aspect to analyze attachment between two groups as the sharing of members [15]. To some extent, this method avoids option 2 by restructuring the network with actors as groups and edges as common members. Contrastingly, the community-structure algorithm used in the present paper yields non-overlapping groups. As a result, we take option 2 by developing a new representation of the groups over time, and we use this representation to observe mechanisms at the group-level which are analogous to the measures at the individual-level. As expected, this representation yields results which are consistent with individual-level mechanisms and the findings of Palla *et al* at the group-level.

For a representation which allows for the characterization of group evolution with non-overlapping groups, a heterarchy of the groups over time is constructed. This heterarchy shows the flow of members through groups over time. More precisely, the heterarchy is a weighted, directed graph where each vertex represents a group, and an edge $e_{(1,2)} = (g_1, g_2)$ exists between vertices g_1 and g_2 if g_1 is a group from the time period directly before the time period of g_2, and members of g_1 are in g_2. The weight of edge $E_{1,2}$ is the number of members from g_1 who are also in g_2. Through this

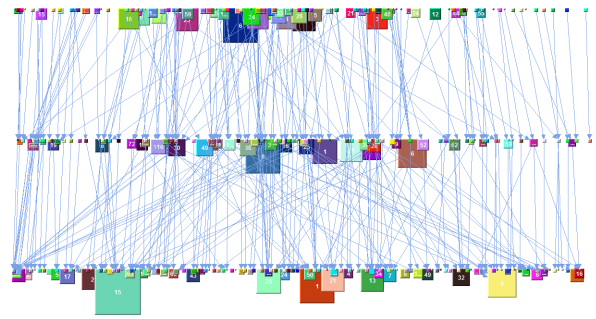

Figure 3: A representation of authors moving through groups over time. Each vertex represents a group, and each edge represents movement from a group in one time period to a group in the next time period.

representation, we observe the fracturing and building of groups over time.

Overall Trends

Before describing the mechanisms by which groups evolve, we first give some general trends for the groups in order to gain a basic understanding of what is occurring across the entire network. First, we find that the network grows over time with groups increasing in average size. In addition, it seems that group members tend to spread apart throughout the network over time. In the following sections, we gain some understanding for the processes which drive these trends. For example, group preferential attachment might explain the increase in average group size and degree over time. At the same time, the fracturing of groups and the diffusion of group members throughout the network might explain the increase in the number of groups over time. In addition, the we will observe the diffusion of group members across the network more precisely through trends in group member interactions over time.

Stability

To gain an understanding of how individuals transfer between communities, we observe the stability of the groups using the time-heterarchy described above. Unsurprisingly, we find that larger groups tend to have less stability. To demonstrate this, we measure stability as the number of groups into which a single group splits over a single time period (or the number of outgoing edges in the *time-heterarchy*), and we correlate this with group size (Figure 4). In addition, fracturing per member is compared to group size (Figure 5), which shows that larger groups tend to stay together in larger clumps.

Group Link Changes

The stability results of the previous subsection suggest that groups tend to disintegrate over time, and new groups emerge from this disintegration. In order to describe this process more specifically, we consider the number of interactions between members of a single group over time, and the number of interactions between members of two groups over time. In both cases, the time-heterarchy is used, where each group-vertex v_i in the heterarchy is assigned a mapping from each group g_j in the *first* time interval (1981-1985) to the number of members n_{ij} of g_j who are also in the group represented by v_i. As a measure of interactions between members of each original group g_j, the aver-

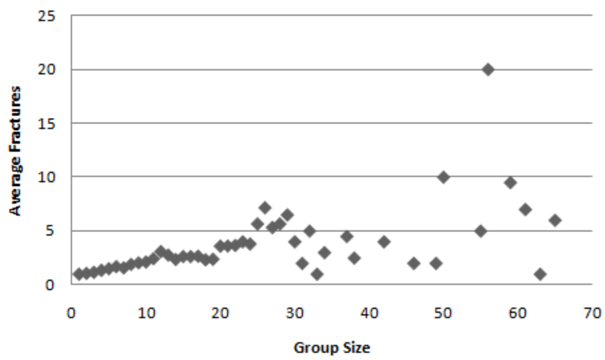

Figure 4: The fracturing of groups correlated with the number of members in each group. A large group of individuals is likely to split into more groups in the next time interval.

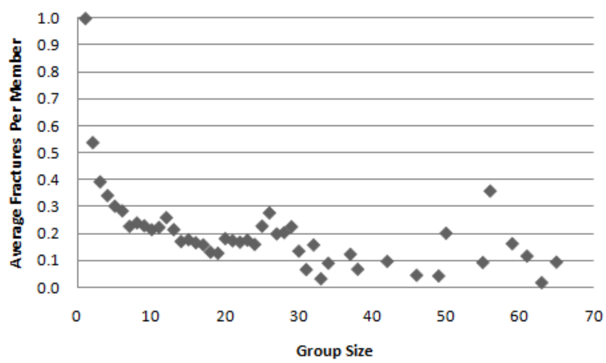

Figure 5: The size of groups correlated with the number of fractures per member. While larger groups are likely to have more splits (as shown in Figure 4), these splits are likely to be composed of a higher number of members.

age of all n_{ij} is computed. Likewise, as a measure of the interaction between two groups, g_j and g_k we take the average of all products $n_{ij} \cdot n_{ik}$.

We find that the average across all n_{ij} is decreasing over time, which implies that a group starts with its members together, and they slowly disperse across the network into separate groups. In the case of two groups' interactions over time, the situation is the same ($n_{ij} \cdot n_{ik}$ decreases). Intuitively, this means that the the members of two groups start to collaborate and form new groups, and then those groups fall apart over time.

Preferential Attachment

Analogous to the individual-degree distribution, group size (number of authors in a group) and group degree (number of edges from a group to other groups) also follow power-laws. Therefore, as Pollner *et al* suggest, preferential attachment might also occur at the group level [16]. In their study, Pollner *et al* test this claim by defining attachment between groups as the sharing of common group members. This method relies on the use of a community structure algorithm which detects overlapping groups. In contrast, we gather evidence for group-level preferential attachment through a method which does not rely on overlap between groups. Specifically, our method regards attachment as the formation of a new group in the next time interval from members of disjoint groups, whereas their study defines attachment as the appearance of connections through shared group membership.

To test our notion of group-level preferential attachment on disjoint groups, we use the *time-heterarchy*. As a modification to the notion of individual-level preferential attachment, we define attachment between two groups g_1 and g_2 in the same time interval to be the formation of a new group g_3 in the next time interval by members of g_1 and g_2. In the time-heterarchy, this attachment is represented by the existence of directed edges (g_1, g_3) and (g_2, g_3). Using this notion of attachment, we find that groups are more likely to attach to groups with a higher number of members. For example, between intervals 1998-2002 and 1999-2003, two groups of size 3 have probability .0002 of attaching whereas a group of size 61 has probability .167 of attaching to a group of size 65. In addition, groups are more likely to attach to groups with a higher group-degree (this is necessary as group degree increases with group size).

Given that members of larger groups tend to have higher degrees, and there are more authors with which to collaborate in bigger groups, preferential attachment at the group-level seems to be reducible to preferential attachment at the individual-level. Still, the extent to which group interactions can be described in terms of member interactions remains unclear. We attempt to clarify this relationship in the next subsections.

Strengthening and Closure

Similarly to the way in which preferential attachment occurs at both the individual-level and group-level, group triadic closure and relationship strengthening also occur in ways which are analogous to the individual-level processes. To observe both group-level processes, the time-heterarchy is used similarly to the way in which it was used for preferential attachment.

First, relationship strengthening between groups is shown by comparing the number of links between two groups with the probability that their members form a new group together in the next time period (this is the same notion of attachment used in group preferential attachment). Predictably, the results show that members of groups with more collaboration at one time period are more likely to form new groups at the next time period. This result also follows from the individual-level mechanisms. Since individuals who collaborate at one time period are likely to collaborate at the next, and they are likely to collaborate with their neighbors' neighbors, they are likely to form *groups* with their neighbors (as both these conditions must hold to form a new group).

In order to measure group triadic closure, a group network is constructed for each time period where each group is a vertex, and two groups are connected by an edge weighted as the the sum of the weight of the links between the members of the groups. Next, the number of paths of length 2 from one group to the next is compared to the probability of attachment (using the time-heterarchy). Since the number of interactions between two groups can vary greatly by the number of interactions between individual members, we also consider the weights of edges between groups when counting the number of paths. In counting the number of length 2 paths, a single path with edges of weights w_u and w_v is weighted by $min(w_u, w_v)$. This weight is used to differentiate between the stronger and weaker

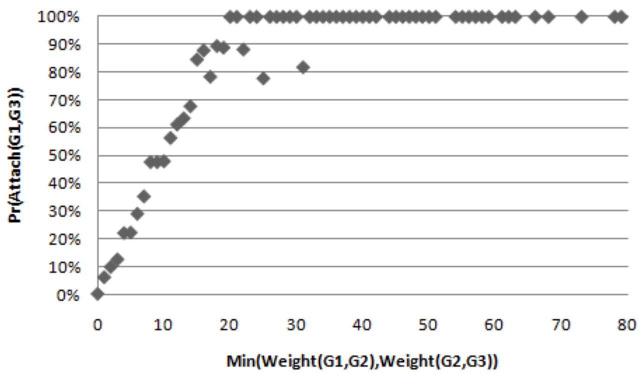

Figure 6: The probability that member of two groups will form a new group given the number of length 2 paths between their groups in the group network.

open triangles between groups. As expected, members of one group are likely to form new groups with members of another group if they share a common neighbor group through many interactions in the previous time interval. This is consistent with individual level triadic closure, since many open triangles are likely to exist amongst individual group members if there is a triangle at the group level.

In the same way that triadic closure and relationship strengthening at the individual-level drive preferential attachment between already existing authors in the network, the similar group-level mechanisms might drive group-level preferential attachment. More specifically, since bigger groups have more connections to other groups, by triadic closure and relationship strengthening, their members are likely to form new groups with other groups. In this sense, these mechanisms provide a bridge between individual-level interactions, group interactions, and group preferential attachment.

Although the group-level triadic closure and preferential attachement seem reducible to their individual-level counterparts, the probabilities of the formations of new relationships at the group-level are much higher than the probabilities at the individual-level. Consequently, models built based on group-level observations might yield more accurate predictions about future relationships. While these predictions might have higher accuracy, they will be less specific, since they will be about groups rather than individuals. For example, based on group-level mechanisms, we might conclude that some members of group g_1 are likely to start collaborating with group g_2 in the future, but we will not be able to say exactly which members will form relationships. In this sense, through the community structure of the network, we are able to smooth its topology and understand how actors function at a higher level.

6. CONCLUSION

In this paper, we first found that the well-known mechanisms of preferential attachment and triadic closure drive our coauthorship network at an individual-level. In addition, we considered individual relationship weight changes to find that authors often increase in the number of papers on which they collaborate, and then they slowly decrease as their relationship diminishes. Next, we found that community structure affects these individual-level mechanisms through the observation that new relationships are more likely to form within groups than outside of groups. Finally, we used the *time-heterarchy* to examine the way in which mechanisms analogous to preferential attachment and triadic closure drive the evolution of the network at the group-level.

Future work could focus on building a model for the evolution of the network at the level of communities based on these results. In addition, it would be interesting to question members of the network to gain an internal perspective on these mechanisms. Also, we could explore the connections between group-level and individual-level mechanisms, and search for group-level phenomena which are difficult to explain in terms of individual-level mechanisms. Finally, using the extra coauthorship-specific assumptions of our community structure algorithm, we can continue to search for relationships between group-level mechanisms and the organization of research.

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