Analyzing Academic Communities' Collaboration and Performance

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Abstract - *Recently, there has been a sharp increase on the scholars' collaborations and there are pros and cons by the effect of scientific collaboration on each scholar' performance. Most of previous researches study the micro-level collaboration network to investigate the effects of scholars' collaboration network structure on their performance but to our knowledge there so few macro-level collaboration network studies to evaluate the association between academic communities network structure and the communities' academic performance. In this study, we analyze scientific collaboration network structure and network attributes of five information schools and test if there is any link between them and their academic performance. Analysis of collected data shows that the communities' which are lower density and lower network degree centrality (more decentralized) have higher performance. This could be as a result of share more redundant knowledge in the dense and centralized scientific collaboration networks, which is an obstacle for innovation and new ideas.*

Keywords: Scientific collaboration networks, co-authorship, academic community performance, social network analysis

1 Introduction

In recent years, there has been a sharp increase in the number of collaborations between scholars especially internationally. An explanation for the rapid growth of international scientific collaboration has been provided by Luukkonen et al. as well as Wagner and Leydesdorff [1-3]. By jointly publishing a paper, researchers show their knowledge sharing activities, which are essential for knowledge creation. As most scientific output is a result of group work and most research projects are too large for an individual researcher to perform, it often needs scientific cooperation between individuals across national borders [4]. Thus, being more conscious of collaborations in science has led to a sharpened focus on the collaboration issue [5]. There are many studies, such as [6, 7], have been confirmed the importance of scientific collaboration of researchers' performance.

Since scientific collaborations are defined as "interactions taking place within a social context among two or more scientists that facilitates the sharing of meaning and completion of tasks with respect to a mutually shared, super-ordinated goal" [8], those collaborations frequently emerge from, and are perpetuated through, social networks. Social network analysis has produced many results concerning social influence, social groupings, inequality, disease propagation, communication of information, and indeed almost every topic that has interested 20th century sociology [9].As social networks may span disciplinary, organizational, and national boundaries, they can influence collaboration in multiple ways [8].

In this paper, we are aiming to find: How to identify and evaluate the research collaboration structure of academic communities? Can communities' collaboration network structure and attributes explain their performance (productivity)? Thus, for our analysis, we use scholars' publication information that is available on five information systems schools (iSchools) in US. After processing the publication information (e.g., title, authors, publish year), we store the data in a relational database and extract and shaped co-authorship networks of each school. Then by calculating collaboration (co-authorship) network measures and their performance measures (through number of citations each publication received), we test to find if there is relation between scholars' collaboration and their performance.

Following reviewing literature on social network analysis by focusing on the (whole) network level (marco-level) analysis and measures, our data collection method and dataset details has been explained followed by methods and measure that we will use in this study. Then, results of calculation of schools' collaboration network citation-based performance and network measures have been shown. The paper ends with conclusions and talking about research limitations and highlighting contribution.

2 Background

Social networks operate on many levels, from families up to the level of nations. They play a critical role in determining the way problems are solved, organizations are run, markets evolve, and the degree to which individuals succeed in achieving their goals [10]. Social networks have been analyzed to identify areas of strengths and weaknesses within and among research organizations, businesses, and nations as well as to direct scientific development and funding policies [8, 11].

A social network is a set of individuals or groups each of which has connections of some kind to some or all of the others. In the language of social network analysis, the people or groups are called ‘‘actors’’ or “nodes” and the connections ‘‘ties’’ or “links”. Both actors and ties can be defined in different ways depending on the questions of interest. An actor might be a single person, a team, or a company. A tie might be a friendship between two people, collaboration or common member between two teams, or a business relationship between companies [9]. In scientific collaboration network actors (nodes) are authors and ties (links) are co-authorship relations among them. A tie exists between each two actors if two scholars have at least a coauthored paper. Constructing collaboration (co-authorship) networks of scholars is widely studied so far [6, 8, 12-19] for different fields of study.

2.1 Social cohesion

Social cohesion is often used to explain and develop sociological theories. Members of a cohesive subgroup tend to share information, have homogeneity of thought, identity, beliefs, behavior, even food habits and illnesses [20]. Social cohesion is also believed to influence emergence of consensus among group members [21]. “Examples of cohesive subgroups include religious cults, terrorist cells, criminal gangs, military platoons, sports teams and conferences, work groups etc“ [21].

Modeling a cohesive subgroup mathematically has long been a subject of interest in social network analysis. One of the earliest graph models used for studying cohesive subgroups was the clique model [22]. A clique is a sub graph in which there is a link between any two actors (vertices). However, the clique approach has been criticized for its overly restrictive nature [20, 23] and modeling disadvantages [24, 25]. Clique models idealize three important structural properties that are expected of a cohesive subgroup, namely: familiarity (each node has many neighbors and only a few strangers in the group), reachability (a low diameter, facilitating fast communication between the group members) and robustness (high connectivity, making it difficult to destroy the group by removing members) [21].

2.2 Network Density

Density describes the general level of linkage among the points (actors) in a network (graph) [26]. The more points connected to one another, the denser the network is. So, the densest network is the one which all points are connected with each other but such a networks are very rare.

2.3 Clustering Coefficients

Mainly networks are clustered which means they possess local communities in which a higher than average number of people know one another. One way to check the existence of such clustering in network data is to measure the fraction of ‘‘transitive triples’’ (also called clustering coefficients) in a network [13]. The clustering coefficients of a network is the fraction of ordered triples of nodes A, B, C in which edges AB and BC are present that have edge AC present. In other words, it is the probability that two neighbors of a vertex adjacent to each other. In other words, clustering coefficient is an important property of networks which is “the probability that two of a scientist’s collaborators have themselves collaborated” [27, 28]. Thus, higher clustering coefficients value means it is significantly common for scientists to broker new collaborations between their co-authors.

2.4 The Giant Component

In small networks (few actors and connections), all individuals belong to small group of collaboration or communication. As the total number of connections increases, however, there comes a point at which a giant component forms, "a large group of individuals who are all connected to one another by paths of intermediate acquaintances" [13]. It is important to realize that the collaboration network is fragmented in many clusters. There are several reasons for this. First, in every field there are scientists that do not collaborate at all, that is they are the only authors of all papers on which their name appears. In most research fields, apart from a very small fraction of authors that do not collaborate, all authors belong to a single giant cluster from the very early stages of the field [28].

2.5 Network Centralities

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 its actors. Actors centrality measures help determine the importance of the actor in the network. Bavelas [29] was the pioneer who initially investigates formal properties of centrality and proposed several centrality concepts. Later, Freeman [30] found that

centrality has an important structural factor influencing leadership, satisfaction, and efficiency.

To examine if a whole network (graph) has a centralized structure. "The concept of density and centralization refer to differing aspects of 'compactness' of a graph (network). Density describes the general level of cohesion in a graph; centralization describes the extent to which this cohesion is organized around particular focal points" [26]. The important node centrality measures are:

2.5.1 Degree Centrality

The degree centrality is simply the number of other points connected directly to a point. Necessarily, a central point is not physically in the centre of the network. Degree of an actor is calculated in terms of the number of its adjacent actors.

2.5.2 Closeness Centrality

Freeman [30, 31] proposed closeness in terms of the distance among various points. Sabidussi [32] used the same concept in his work as 'sum distance', the sum of the 'geodesic' distances (the shortest path between any particular pair of points in a network) to all other points in the network. A point is globally central if it lies at the shortest distance from many other points which means it is 'close' to many of the other points in the network. So, simply by calculate the sum of distances of a point to others we will have 'farness', how far the point is from other points and then we need to use the inverse of farness as a measure of closeness. As in unconnected networks every point is at an infinite distance from at least one point, closeness centrality of all points would be 0. Thus, Freeman proposed another way for calculating closeness of a point by "*sum of reciprocal distance*" of that point to any other points.

2.5.3 Betweenness Centrality

Freeman [30] yet proposed another concept of centrality which measures the number of times a particular node lies 'between' the various other points in the network (graph). Betweenness centrality is defined more precisely as "the number of shortest paths (between all pairs of points) that pass through a given point" [33].

2.5.4 Eigenvector Centrality

Eigenvector centrality assigns relative scores to all actors in the network based on the principle that connections to high-scoring actors contribute more to the score of the node in question than equal connections to low-scoring actors. Based on the idea that an actor is more central if it is in relation with actors that are themselves central [34], it is arguable that the centrality of some node does not only depend on the number of its adjacent actors, but also on their value of centrality. Bonacich [34] defines the centrality c(vi) of a node vi as positive multiple of the sum of adjacent centralities.

2.6 Community (group) Performance

A community can be any group of individuals. In the research context, an individual (i.e. scholars) can belong to different communities. For example, at a university, we can distinguish, in hierarchical order, research groups, departments, schools, colleges, and the entire university. Such a hierarchical classification allows comparing the performance of communities at different levels but here we consider each school as a community (group) and compare their performance.

To assess the performance of scholars, many studies suggest quantifying scholars' publication activities as a good measure for the performance of scholars. The general idea is that a researcher gets a high visibility in the research community, if the researcher publishes and her publications get cited. The number of citations qualifies the quantity of publications [35]. Hirsch [36] introduced the h-index as a simple measure that combines in a simple way the quantity of publications and the quality of publications (i.e., number of citations). A scholar with an index of h has published h papers, which have been cited by others at least h times. The h-index is also being used by many academic databases (e.g., Web of Science and Scopus) to measure the performance of scholars. Furthermore, the h-index became also the basis for a wide range of new measures [37-42].

There are some studies that suggest measures for evaluating the output of research communities by extending the previously mentioned indices to groups [37, 40, 43-45]. For instance, Prathap (2006) used h-index basic and defined h1-index (h1 papers which have at least h1 citation) and h2-index (h2 researchers who have at least h-index of h2) to quantify the performance of the institutes. Also, some more successive h-indices were defined for measuring journal, publishers and countries, level-wise (Schubert, 2007; Braun et al., 2005). Also Tol (2008) defined g1-index as a successive g-index factor (g1 department members that have a g-index of at least g1 on average).

3 Data and Methods

3.1 Data Sources

For this study, we collected data on five information schools (iSchools): University of Pittsburgh, University of Berkeley, University of Maryland, University of Michigan, and Syracuse University. These schools have been chosen, since they offer similar programs in the area of information management and systems and, because of the fact, that the topic of these schools is new within the university landscape.

The data sources used are the school reports, which include the list of publications of researchers, DBLP, Google Scholar, and ACM portal. Citation data has been

taken from Google Scholar and ACM Portal, using AcaSoNet [10]. AcaSoNet is a Web-based application for extracting publication information (i.e., author names, title, publication date, publisher, and number of citations) from the Web. It also extracts relationships (e.g., co-authorships) between researchers and stores the data in the format of tables in its local database.

For its citation counting service, Google Scholar considers a variety of publication databases, which belong to different publishers and list different types of publications. Thus, it produces a higher publication count per researcher and a higher citation count per publication than other citation counting services (e.g., Web of Science of Thomson Reuters, and Scopus) [46]. Consequently, the calculation of the the g-index, if based on Google Scholar, results in higher values than for the other citation counting services. However, Ruane and Tol show that rankings based on Google Scholar have a high rank correlation with rankings based on Web of Science or Scopus [47].

For our analysis, we followed Google Scholars approach and did not differentiate between the different types of publications. Our data covered a period of five years (2001 to 2005), except for the University of Maryland iSchool, which had no data for the year 2002 in their report. To resolve this issue, we substituted the missing data with data of the year 2006.

Despite AcaSoNet, much data cleansing has become necessary in order to allow processing of the extracted publication data. Most of the cleansing was due to the lack of a standard format used for listing publications (e.g., the order of first name and family name of authors, the order of title and publication year and the inaccuracy in writing journal and conference names). After the cleansing of the publication data of the five iSchools, 2122 publications which have received totally 31100 citations, 1806 authors, and 5310 co-authorships were finally available for our analysis.

3.2 Methods and Measures

In this study, we will evaluate networks (groups) measures for five different information schools and compare their group productivity (performance). We apply network (group) level of social network analysis by measuring some quantities of collaboration networks: cohesion measures (e.g., density, clustering coefficient, and distance), region measures (e.g., number of components and blocks) and group centrality measures (e.g., degree, closeness, betweenness and eigenvector centralities). we also measuring some other quantities of collaboration networks using UCINET [48].

3.2.1 Network Density

Simply density of a network is the proportion of exiting links to the maximum possible distinct links that could be exists.

3.2.2 Clustering Coefficients

The clustering coefficient, a quantitative measure of this phenomena, C, can be defined as follows [49]: if node i that has links to k_i other actors in the system. If these k_i actors form a fully connected clique, there are $k_i (k_i - 1)/2$ links between them, but in reality we find much fever. Let us denote by N_i the number of links that connect the selected k_i actors to each other. The clustering coefficient for node i is then $C_i = 2N_i / k_i (k_i - 1)$. The clustering coefficient for the whole network is obtained by averaging C_i over all actors in the system. In simple terms the clustering coefficient of a node in the co-authorship network tells us how much a node's collaborators are willing to collaborate with each other, and it represents the probability that two of its collaborators wrote a paper together [28].

3.2.3 Network Centrality Measures

A network centralization measure indicates how tightly the network is organized around its most central points. So, the general view is finding differences between most central points' centrality scores and others'. Then, centralization calculated as a ratio of sum of these differences to the maximum possible sum of differences. So, to calculate network centrality measures first step is to find all actors measures and then find the whole network centralities measures.

3.2.4 Community (Group) Performance

In order to measure community performance, we use a variant of g-index (g1-index) by Tol (2008) which defined as a successive g-index factor (g1 community members that have a g-index of at least g1 on average). It can be calculate using similar formula of Egghe's [38] g-index but considering on the g-index of scholars in a community rather than citations of publications. For communities having equal g1-index value, we use the average of g-index indices of g1 scholars in the community (g1a-index).

4 Analysis and Results

Table 1 includes detail statistics of the performances measures (e.g., g1 and g1a), number of publications, sum of citations, number of authors and number of collaborations for each school separately. The results based on number of publication, authors and citation indicate that Michigan's scholars had published more than others following by Pittsburg and Berkeley with just few differences (490, 477 and 468 respectively) while in terms of number of citations those publications received Michigan has the most (10962) with a big gap following by Berkeley (7544) and others. As it is shown the number of authors of Michigan is much higher than others. So, considering average number of citations received per author, Berkeley will be ranked first and then Michigan while considering average number of citations per

publications Michigan is ranked first and then Berkeley (similar to total number of citations).

From seventh row to the end of the Table 1, the value of different network measures, which has been discussed in section 3.2, have been shown. Based on the number of actors and links for each school, Michigan and Pittsburg are the densest co-authorship networks and Berkeley and Syracuse have the least. As it is expected, Michigan has the most number of blocks, components and cliques and also average distances among the connected actors (due to having high number of actors and links). Considering clustering coefficient, Pittsburg and Berkeley authors' co-authors are more willing to collaborate with each other (the probability that two of its co-authors wrote a paper together is high). Thus, it will lead to a denser network.

The communities (schools) have been ranked based on their citation-based performance index (g1-index and g1a-index), the same order from left to right in Table 1. While the number of communities (schools) that we analyze is not enough to infer a statistical conclusion about the association between collaboration networks aspects and communities' performance but we find that density have almost a negative relation, the less dense the school the better performance (except for Berkeley which has the second highest density value while they are in the second order). Network degree centrality also shows almost a negative relation, as almost schools with lowest degree centralities have better performance and vice versa (except for Pittsburg).

The results confirmed that the networks with more collaboration (links) have more blocks, components and cliques. Also, the networks with higher number of actors and links have higher network eigenvector and betweenness centrality measures. But interestingly, Berkley with fewest scholars and collaborations (actors and links) are ranked second in terms of performance.

Maryland iSchool is the most central network in terms of degree and closeness network centrality measures and Michigan is the most central in terms of betweenness and eigenvector centralities. Figure 1 and 2 shows Berkeley and Michigan collaboration networks (the least dense and densest networks respectively) as an example. The components are differentiated with different colors. As we can see in the two sample networks there are some broker scholars who connect sub-groups of scholars which otherwise disconnected.

Table 1. Schools' network measures

Measures	Michigan	Berkeley	Syracuse	Pittsburg	Maryland
Performance (g1-index)	**19**	**17**	**15**	**15**	**14**
g1a-index	212.78	124.42	141.40	136.87	130.93
Number of papers	490	468	375	477	312
Sum of citations	**10962**	**7544**	**4917**	**4410**	**3267**
Number of authors (actors)	603	262	280	358	303
Number of collaborations (links)	1486	864	873	1147	907
Density	.016	.032	.024	.025	.035
Average Distance	4.567	3.341	4.077	4.447	3.258
Clustering Coefficients	.814	.821	.664	.898	.696
Number of Blocks	136	64	102	107	57
Number of Components	17	8	11	12	9
The Giant Component	472	130	242	273	252
Number of Cliques	201	84	93	110	118
Network Centrality Measures					
Degree	.012	.022	.026	.018	.036
Closeness	.407	.309	.380	.326	.536
Betweenness	.410	.107	.284	.249	.345
Eigenvector	.841	.031	.025	.783	.036

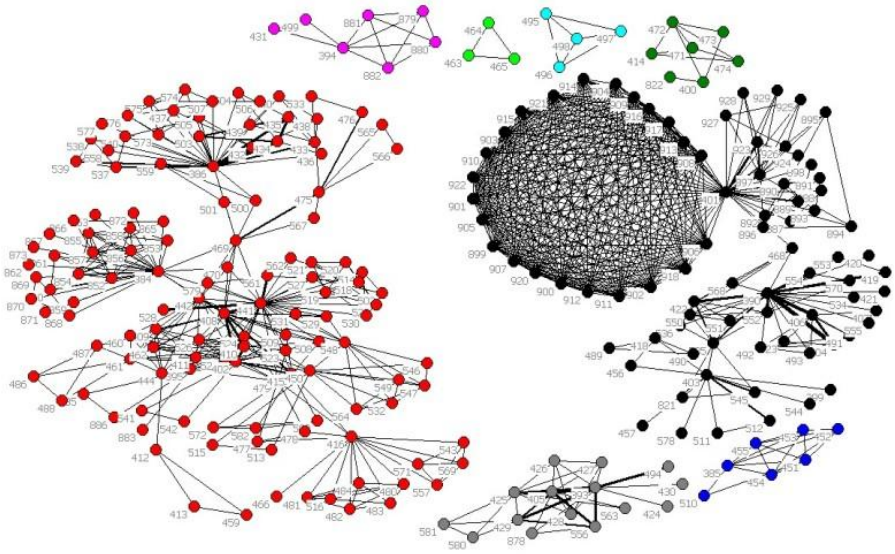

Figure 1. Berkeley co-authorship network and its components

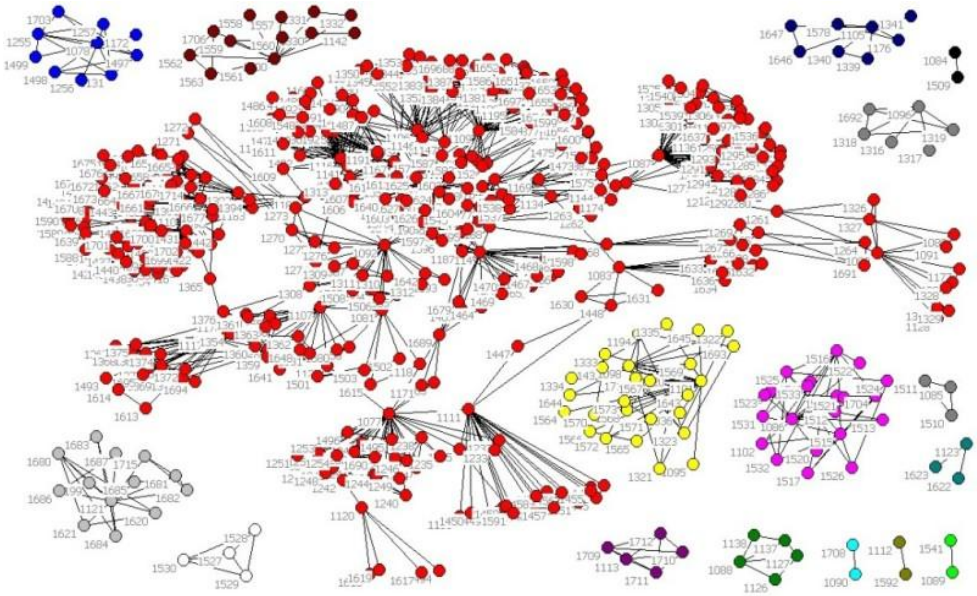

Figure 2. Michigan co-authorship network and its components

5 Conclusion

We analyzed five information schools collaboration network structure in terms of density, number of cliques, blocks, components and network centrality measures. Schools with more authors and collaborations show better eigenvector and betweenness centrality measures. Calculating schools' citation-based performance output using bibliometric indicators (g1-index); we find that network density and degree centrality have almost negative relation with communities' performance. This could be as a result of share more redundant knowledge in the dense and centralized scientific collaboration networks, which is an obstacle for innovation and new ideas. However, with just few communities we have analyzed their performance and network attributes we cannot infer a general conclusion about the relation between network performance and

network measures and attributes. This can be considering as our research limitations.

We know that the extent to which researchers co-authors vary among scientific fields and it is usually assumed that this is caused by variation in the level of collaboration. To investigate how scientific field (due to their different collaboration characteristics) influence on the association of researchers' collaborations activities and their performance, it is a need to do similar analysis for several research collaboration groups from different fields as a future work. As this study evaluate the static collaboration network, another extension of this work could be studying dynamicity of the collaboration network and investigate the networks evolutionary changes on their performance.

6 References

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