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Mining and Analyzing Academic Social Networks

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Abstract: Academics establish relationships by way of various interactions like jointly authoring a research paper or report, jointly supervising a thesis, working jointly on a project, etc. Some of these relationships are ubiquitous whereas other are hard to keep track of. Of all types of possible academic and research collaborations, co-authorship is best documented. In this paper we analyze the co-authorship based academic social networks of computer science engineering departments of Indian Institutes of Technology (IITs) as evidenced from their research publications produced during 2011 and 2015. We use social network analysis metrics to study the collaboration networks in four leading IITs. From experimental results it can be concluded that IIT Delhi and IIT Kharagpur have a close knit collaboration network whereas the collaboration network of IIT Kanpur and IIT Madras is fragmented. However, the collaboration networks of all the four IITs exhibit similar network properties as expected from any other collaboration network.

Keywords: Social Networks, Co-authorship Networks, Social Network Analysis, IITs

1. INTRODUCTION

Publishing research work is one of the primary activities of academics. These publications are intellectual contributions in terms of ongoing or completed work of one or more people [1]. Sharing of ideas has traditionally proven to contribute immensely to existing knowledge. This is truer in case of science. Studies [2] point towards dominance of sole author publications in the beginning of the 20th century whereas, the trend got reversed with the passage of time [3] as the percentage of sole author publications took a plunge. The rise in number of co-authors of a publication is the need of modern day research as it has become more specialized; requires clear understanding of underlying concepts of diverse subjects; has to be interdisciplinary in nature, etc. [1]. It therefore becomes next to impossible for a single person to deal with all aspects of a problem and he has no choice but to seek support and work with other people in a team setup.

In an online social network environment users establish relationships by sharing status, by way of likes, or tweets and retweets. However, these relationships are casual, whereas, on the other hand, the relationships between researchers established through various academic activities are much more formalized [4]. There are a number of ways in which academics collaborate and establish academic relationships but co-authorship is the most tangible and well documented form of research collaboration [5]. By means of being co-authors academics forms social networks [4]. In order to extract and study these networks the co-authorship data has to mined, processed and used. Digital libraries like DBLP, Microsoft Academic Search provide a rich source of co-authorship information and make it available online. In addition, institutional websites also serve as a rich source of co-authorship information on people working with that institution. Analysis of these co-authorship relationships provides a lot of information about individuals, groups and institutions.

Orgnet.com1 defines social network analysis (SNA) as a tool for analyzing relationships and flows between various entities like people, groups, organizations, computers, URLs, etc. As discussed in [5], in social networks, nodes represents entities like people, groups, organizations, etc. whereas, the edges represents the relationships or flows between the nodes. Using SNA techniques one can have both a visual and a mathematical analysis of relationships in social networks.

Study of the patterns of interaction and communication in collaborations between various actors has already attracted significant interest from scholars [6, 7, 8, 9]. Advances in data mining and recent developments in social network visualization software have facilitated the study and analysis of intensity and dynamics of these relationships in a visual or graphical manner [9]. Representation of interactions between entities in terms of nodes and edges i.e. graphs, where nodes represents entities and edges represents interactions, allows one to apply graph theory for the analysis and understanding of underlying collaborations [9]. Such a study is capable of finding and describing the interactions at micro, macro and universal level.

In this paper, we discuss the extraction of collaboration networks to study co-authorship collaborations of people of computer science engineering departments of four Indian Institutes of Technology (IITs) over a five year period. Like any other graph the collaboration network is essentially a graph represented as (G=V, E), where the vertices (V) represent authors and the edges in the edge set (E) represents the co-authorship link between these authors. Each edge (e) has certain weight that represents the frequency of joint authorships i.e. papers written jointly by a pair of authors.

The paper is organized as follows: In section 2, we discuss background and related work in the area. We discuss our data collection in section 3. In section 4, we discuss social network extraction and visualization. In section 5, we discuss social network analysis metrics we concentrate on in this work. We present and discuss our experimental results in section 6. Finally, we conclude and give some future directions in section 7.

2. RELATED WORK

Automatic techniques for social network extraction are not that old with the first one proposed in the year 1997 [10]. It was the first attempt of its kind to develop an automated interactive tool for extraction of social networks formed by

[1] Orgnet.com: http://www.orgnet.com/sna.html

people of a specific domain. Since then a number of such efforts have been made to automatically extract underlying social networks from a multitude of data sources. A detailed discussion on the social network extraction methods has been provided in [11].These methods have been classified in [11] on the basis of the type of the information source used for extraction of relationships and in turn the social networks.

Co-occurrence of names on the web returned by a search engine in response to a query has commonly been used by social network extraction methods [10, 12, 13] to quantify the strength of relation between two names. Referral Web [10] extracts egocentric social networks by using co-occurrence of any two names in publically available online documents like homepages, publications, citations, etc. Domain specific social network extraction has been performed by some studies [13, 14], where [14] extracts social network formed by conference participants and [13] extracts social networks of online Semantic Web community.

In addition to co-occurrence based academic social networks some studies like [15] uses this measure to extract social networks from news articles Majority of the co-occurrence based methods proposed in the literature used co-occurrence based metrics to compute the weight of the extracted relations among entities but few of them have examined how to weigh each relation among entities beyond the co-occurrence based metrics [12]. Oka and Matuso [16] propose a method for weighting the relation among entities based on the weight of relations through the keyword, overcoming the shortcomings of the co-occurrence based metrics. The method receives a pair of entities and various relations that exist between entities as input. The output is the weight value for the pair of entities according to the generality of the keyword as a measure of its web hit counts.

There are a number of studies which concentrate on extraction of various types of social networks from different types of online data sources. Because of space constraints we cannot discuss all of them here but readers interested in the same can refer to [11].

The focus of the techniques discussed earlier in this section is extraction of social networks however they do not provide any analysis of these networks. In essence these networks are a result of some collaboration between the entities involved and their study from a network perspective may unravel some interesting facts about their structure, flow of information, important actors in the network, etc.

In addition to extraction of social networks some studies have tried to analyze and predict the evolution of collaboration networks in the scientific domain [5]. Some of them [17, 18, 19, 20] have tried to investigate their behavior in terms of their being small-world, scale-free, following power-law, etc. in addition to indentifying important actors in the network through parameters like betweenness centrality, vertex centrality etc. Analysis of these parameters provides a good insight of the health of the research community and the institution [5]. Better the academic and research activities in a group, community or an institution, the better their health.

Co-authorship being the most tangible and documented form of academic collaboration has the potential of being a true representative of academic collaborations. Thus co-authorship network can be considered as a true representative of academic social networks of people involved. Some studies [17, 18, 19, 20, 21, 22, 23, 24] have analyzed co-authorship networks across several domains like Biology, Computer Science, Mathematics, Physics, Social Science, Database, Digital Library, etc.

Study of the cooperation through co-authorship relationship using social network analysis measures has been made in specific domains like journals and conferences. Networks formed in Chinese humanities and social science [25] in DBLP listed conferences viz. KDD, VLDB, ICML and WWW [26], in specific venues like IC3 [27] in Scientometrics Journal [28], etc.

3. DATA

The data for the purpose of this study are mined primarily from websites of four IITs. These IITs are IIT Kanpur, IIT Delhi, IIT Kharagpur and IIT Madras. We extracted faculty list and publications of each of these faculty members who are currently on the roll of Computer Science Engineering departments of these four IITs as full time faculty. The period of investigation has been restricted for five years from 2011 to 2015. Publications data of these faculty members were extracted either from their homepages or from some indexing service. Wherever, this data was not available on their homepages directly, it was mined from DBLP. This data was not in a condition that it could have been used directly for analysis purposes. It was first cleaned and data from all the sources brought in a common format so as to make it useful for any further processing.

In all we extracted 1082 publications of 111 faculty members published from 2011 onwards. The statistics of the dataset for the corresponding period are listed in Table-1.

Table 1. Statistics of the dataset.

IIT	Faculty	Number of Publications in					Total
		2011	2012	2013	2104	2015	
Kanpur	25	17	42	27	14	3	103
Delhi	27	62	71	72	69	14	288
Kharagpur	32	40	69	70	20	1	200
Madras	27	113	116	126	108	28	491
Total	**111**	**232**	**298**	**295**	**211**	**46**	**1082**

4. SOCIAL NETWORK VISUALIZATION AND ANALYSIS

In order to convert joint publications into a collaboration network, the publications data has to go through a number of steps. Algorithm-1 provides an overview of the major steps involved in the process of transforming raw publication data into social network graphs. The same algorithm can be repeated for any number of institutes.

From an abstract point of view the steps involved in the social network extraction process can be viewed as shown in Figure-1. After data cleaning name disambiguation is performed in order to remove duplicates, if any. From these cleaned co-authors list co-author relations are extracted. We implemented this algorithm in Java.

Once these publications were brought in a common format, list of all the authors for each of the publications were extracted. Before extraction of co-authorship relationships from these author lists duplicate names has to be removed otherwise we may not be able to either visualize or analyze these co-authorship networks correctly. In addition, these duplicates may also hamper the analysis of the research productivity of individual researchers. Removal of duplicates or name disambiguation plays an important role in efficient analysis of publications data. In case of academic social network analysis name disambiguation plays a very crucial role. A detailed discussion on name disambiguation techniques has been provided in [29]. We use a modification of vector space model based name disambiguation technique provided in [30].

Algorithm-1: Social Network Extraction and Visualization.

Step-1 Extract faculty list from homepage of the department.

Step-2 ***for each*** faculty extract publications from his homepage or DBLP

Step-3 Clean and normalize these publications

Step-4 ***for each*** publication in the publications list extract the list of authors

Step-5 Perform name disambiguation and extract co-authorship relationships from these publications

Step-6 Extract social networks from these co-authorship relationship

Step-7 Visualize and analyze these social networks using a network graph visualization engine.

After performing name disambiguation, co-authorship relationships from each of the author lists were extracted. These relations were exported to NodeXL. NodeXL converts these co-authorship relationships into network graphs which render themselves to visual analysis. Social network metrics discussed in [5] and some others were obtained from graph metric calculation facility provided in NodeXL.

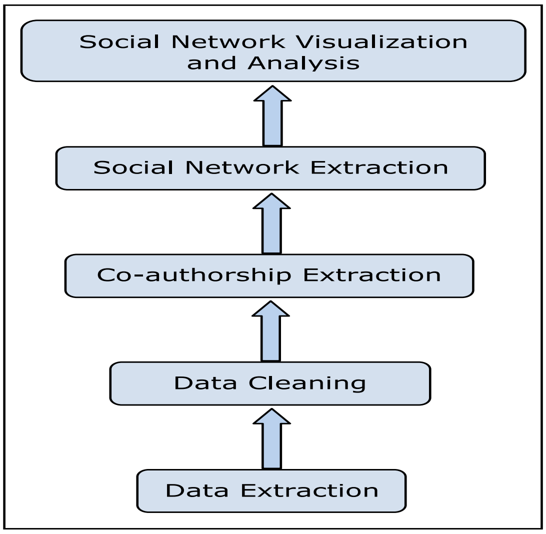

Figure 1: Workflow of the proposed social network extraction and visualization system.

5. SOCIAL NETWROK ANALYSIS METRICS

According to [31] the levels of social network analysis are actor, dyadic, triadic, subset, or network. Metrics like centrality, prestige and roles such as isolates, liaisons, bridges, etc. are used to analyse the social network at actor level, whereas distance and reachability, structural and other notions of equivalence, and tendencies toward reciprocity are important at dyadic level. At triadic level one is interested in balance and transitivity. At subset level one is interested in finding cliques, cohesive subgroups, components whereas metrics like connectedness, diameter, centralization, density, prestige, etc. are used for analysis at network level [32].

Social network metrics, such as, centrality measures [33] (degree centrality, betweenness centrality, closeness centrality and network centrality), average degree, clustering co-efficient, Salton index, density and characteristic path length are often of great interest to the analysis of academic or research collaboration from a network perspective. The study of social networks and their associated metrics is important as these networks form the underlying structure, which allows for rapid information distribution [34].

Several network analysis measures as proposed in [35] can be used to identify influential nodes and discover community structures of the extracted social networks. We are interested in capturing the internal connectivity as well as attributes of key nodes in the network. In order to identify the leaders in the network, the quantity of interest in many social network studies is the “betweenness centrality” of an actor ‘i’. Centrality is a measure of the relative importance of nodes and edges in a graph [33]. Several centrality measures like “betweenness centrality”, “closeness centrality” and “degree centrality” have been proposed in [35] to identify the most important actors (leaders) in a social network.

The objective of this study is to identify important actors like hubs/leaders, author having most number of connections, strength of collaboration ties, connectivity of authors, etc. using social network analysis metrics.

6. RESULTS AND DISCUSSIONS

The institutional networks presented in this section provide an insight into the amount of research activity being carried out by them. Simple metrics, like number of papers published by faculty in an institution, give some idea about the amount of research activity being carried out. However, advanced metrics like clustering coefficient provide an idea about the connectivity between various actors and cohesiveness of the network.

Table-2 lists the values of various network metrics for the co-authorship based social networks of IIT-Delhi, IIT-Kanpur, IIT-Kharagpur and IIT-Madras presented in Figures 2, 3, 4 and 5, respectively.

These values have been obtained using Graph Metrics Calculator available in the NodeXL Microsoft Excel Template [36]. NodeXL is an open source interactive network visualisation and analysis tool that uses MS Excel as the platform for visualization and analysis of networks using relationship data.

The values of various metrics listed in Table 2 provide important information, inter alia, on the structure of the network, connectivity in the network and patterns of communication. For example, from the analysis of the values of Average Clustering Coefficient listed in this table, it can be observed that it is highest for IIT-Delhi followed by IIT-Kharagpur. This also gets verified from the value of Connected Components for these two IITs. All these four collaboration networks exhibit Small World behavior because the degree-of-separation (Average Geodesic Distance in Table-2) in all the cases is less than six.

Although visual picture may present IIT-Madras as most dense but IIT-Kharagpur has highest density followed by IIT-Kanpur. IIT Delhi has the lowest density of all the four graphs.

Table-2: Values of various metrics for co-authorship networks of the four IITs.

Metrics	IIT			
	Delhi	Kanpur	Kharagpur	Madras
Vertices	399	144	243	567
Total Edges	1949	312	1232	1982
Maximum Geodesic Distance	7	4	10	11
Average Geodesic Distance	3.9513	1.7417	4.0214	5.0033
Graph Density	0.0015	0.0235	0.0239	0.0082
Maximum Degree	61	23	34	90
Average Degree	6.085	3.361	5.811	4.667
Max. Betweenness Centrality	21825.4	300.2	5400.0	80320.6
Avg. Betweenness Centrality	503.80	5.125	324.63	897.282
Maximum Closeness Centrality	0.2	1.0	0.5	1.0
Average Closeness Centrality	0.004	0.159	0.01	0.01
Max. Eigenvector Centrality	0.05	0.123	0.035	0.076
Avg. Eigenvector Centrality	0.003	0.007	0.004	0.002
Maximum PageRank	7.364	4.759	6.448	17.915
Connected Components	3	20	3	7
Max. Vertices in a Connected Component	368	28	228	503
Max. Edges in a Connected Component	1781	70	1162	1754
Average Clustering Coefficient	0.859	0.766	0.807	0.775

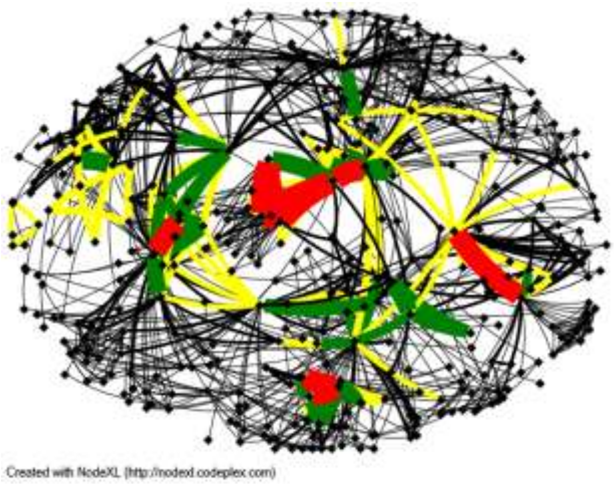

Figure 2: Co-authorship network of IIT-Delhi

In case of IIT-Delhi Aaditeshwar Seth has highest Degree followed by Vinay J. Ribero, Kolin Paul, Smruti R. Sarangi and Amit Kumar. Amit Kumar has highest Betweenness Centrality followed by Vinay J. Ribero, Smruti R. Sarangi, Aaditeshwar Seth and Amitabha Bagachi. In addition to being the node with highest Degree Aaditeshwar Seth has highest Eigenvector Centrality as well as highest PageRank. Although Amit Kumar acts as bridge in the network Aaditeshwar Seth is highly connected with strong connections.

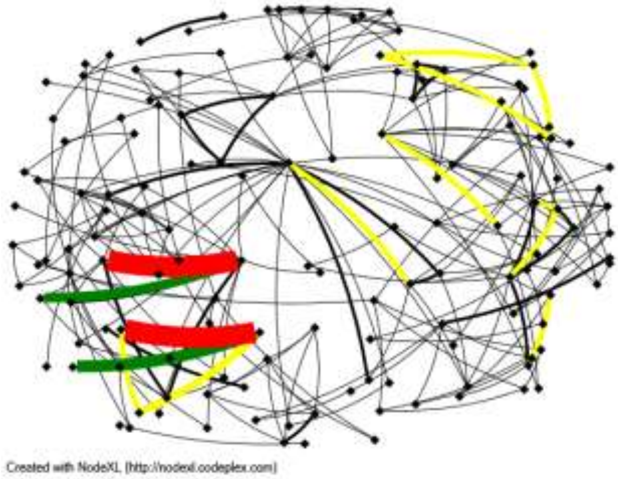

Figure 3: Co-authorship network of IIT-Kanpur

Arnab Bhattacharya has highest Degree in collaboration graph of IIT-Kanpur. He is followed by Phalguni Gupta, Surender Baswana, Harish Karnick and Amey Karkare in terms of Degree. Arnab Bhattacharya has highest Betweenness Centrality also followed by Akshay Mittal, Surender Baswana, Subhajit Roy and Harish Karnick. Arnab Bhattacharya also enjoys the status of having connections with other influential people in the network as he has highest Eigenvector Centrality as well as highest PageRank. Values of these metrics indicate that Arnab Bhattacharya acts as bridge in the network, has most number of connections and has strong connections in the network.

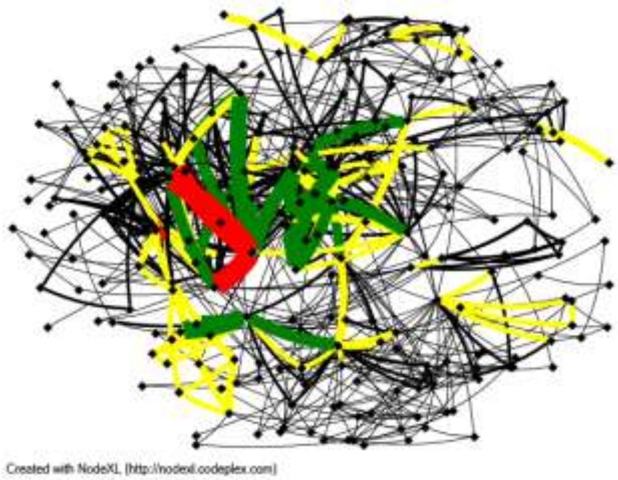

Figure 4: Co-authorship network of IIT-Kharagpur

In collaboration network of IIT-Kharagpur five persons having highest Degree are Pallab Dasgupta, Niloy Ganguly, Rajib Mall, J. Mukhopadhyay and J. Mukherjee respectively. Ansuman Banerjee has highest Betweenness Centrality followed by Rajib Mall, Sukanta Bhattacharya, Santosh Ghosh and Pallab Dasgupta. A. K. Majumdar has highest

Eigenvector Centrality but Rajib Mall has highest PageRank. This implies that Pallab Dasgupta has highest number of connections but A. K. Majumdar has strong connections i.e. connections with influential people in the network. Ansuman Banerjee acts as bridge in the network and Rajib Mall commands highest prestige.

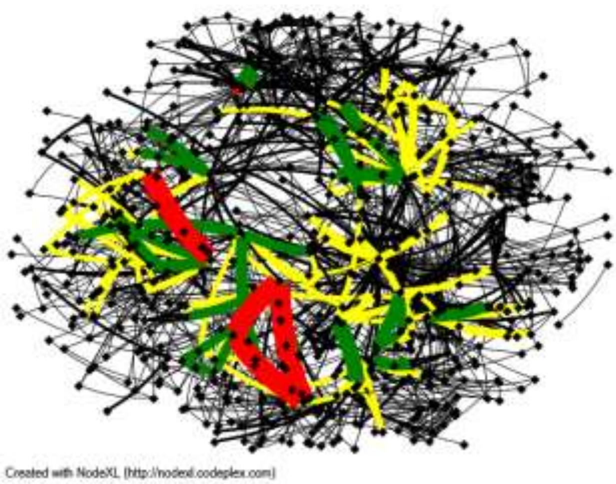

Figure 5: Co-authorship network of IIT-Madras

In this case Balaram Ravindran has highest Degree followed by Krishna M. Sivalingam, C. Pandu Rajgan, N. S. Narayanaswamy and C. Siva Rama Murthy. Similarly Balaram Ravindran has highest Betweenness Centrality. He is followed by N. S. Narayanaswamy, Sutanu Chakarborti, C. Pandu Rajgan and C. Siva Rama Murthy. C. Chandra Sekhar has strongest connections as he has maximum Eigenvector Centrality whereas Balaram Ravindran enjoys highest prestige in the network as he has highest PageRank. This implies that Balaram Ravindran has most number of connections in addition to being the bridge of the network.

In all of the four collaborations graphs differently coloured edges have been used. Red indicates strongest ties followed by Green, Yellow and Black. Black indicates weak ties. The width of the edges also complements the colour edges used in exhibiting the strength of collaboration ties.

7. CONCLUSIONS & FUTURE DIRECTIONS

Social network analysis has been used quite often in the past to study patterns of interaction among various entities including academic ones. In this work we extracted and analyzed co-authorship based collaboration networks of four leading IITs. It can be concluded that IIT Madras has been leading all the four IITs in terms of number of papers produced, per-capita productivity, etc. IIT Khargapur has a different network structure as compared to the rest of three as four different actors enjoy highest values for four different metrics on the basis of which we compare and contrast these collaboration networks.

As a part of future work we would like to extract social network on yearly basis and study the evolution of collaboration networks. We can also extract and analyze local collaborations between people from within a particular department. Another direction could be to study the collaborations between these four institutes.

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