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Ximeng Chen
Sacred Heart University, chenx2@sacredheart.edu

Yiding Cao
Binghamton University, SUNY, ycao20@binghamton.edu

Jiachen Liu
China Galaxy Securities, blackyljc@163.com

Danushka Bandara
Fairfield University, dbandara@fairfield.edu

Hiroki Sayama
Binghamton University, SUNY, sayama@binghamton.edu

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Exploring Social Networks: An Analysis of Intra-organizational Networks

Ximeng Chen[1*], Yiding Cao[2], Jiachen Liu[3],
Danushka Bandara[4] and Hiroki Sayama[2]

[1] Sacred Heart University, Fairfield, USA
[2] Binghamton University, Binghamton, USA
[3] China Galaxy Securities Co., Ltd., China
[4] Fairfield University, Fairfield, USA

[*] chenx2@sacredheart.edu

Abstract

This research investigates intra-organizational social networks by employing network science methods, aiming to provide actionable insights for both managers and employees. Using datasets from the Colorado Index of Complex Networks (ICON), this study examines four intra-organizational networks from a consulting firm and a research team, focusing on advice requests and skill awareness. The analysis includes network topology, degree distribution, community detection, correlation between communities and node attributes, maximal clique detection, and multilayer network analysis. The findings reveal that intra-organizational networks are intricate and significantly impact organizational efficiency and individual career development. Key insights include the importance of mid-level employees in network connectivity, the existence of "bad edges" where advice is sought from less competent peers, and the influence of regional and locational factors on communication patterns. The study emphasizes the need to enhance knowledge sharing and inter-region communications. For employees, understanding the structure of these networks can guide them to more effectively leverage their social connections for career advancement. This interdisciplinary effort bridges gaps in the existing literature and showcases the potential of integrating network science methods into social science research.

1. Introduction

Social and natural sciences have a tradition of studying networks following different approaches. Social scientists aim to understand how social phenomena lead to dynamical network structures, while natural scientists focus on developing generalizable network characteristics that do not necessarily depend on contexts (Hidalgo, 2016). However, these two bodies of literature have great potential to be unified since standard methods and research topics exist (Hidalgo, 2016). In recent years, network science has witnessed a trend of collaborative work between social science and natural science. The current research is also an interdisciplinary effort in which we explore intra-organizational social networks using cutting-edge network science methods. The data we use is retrieved from The Colorado Index of Complex Networks (ICON) by Cross and Parker (2004). The goal of this research is to utilize methods from complex systems to explore the meanings of intra-organizational networks to make recommendations for managers and general employees on how to utilize the capacity of social networks on both individual level and organizational levels. This research also aims to set an example of utilizing advanced network science methods to study social science research questions.

2. Literature Review

2.1 The importance of intra-organizational networks

When thinking about an organizational structure, one usually thinks first of a formal structure, which indicates the hierarchical layout relates to positions. There is another structure within any organization that is not as visible as an organizational chart, what is called the hidden power by Cross and Parker (2004); we call it intra-organizational networks.

Intra-organizational networks refer to information flow and web of relationships within organizations (Cross & Parker, 2004). For managers, it is meaningful to understand how work is really getting done since knowing the hidden structure would inform managerial decision-making to promote efficiency (Cross & Parker, 2004). For employees, these informal networks are usually influential in their productivity, learning, and career success since they largely determine whom they would go to for advice (Cross & Parker, 2004).

Intra-organizational networks contain different types of relationships. To name a few: formal communication, informal communication, information sharing, advice seeking, role awareness, and trust. All these different types of networks exist within the same group of individuals who are all employees of a particular organization. An awareness network, for example, indicates whether the employees of an organization are aware of each other's roles, skills, and knowledge. As another example, the advice-seeking network illustrates how employees would seek advice when they encounter concerns or problems at work.

These networks imply valuable organizational knowledge since they unfold the hidden structures. For instance, Zagenczyk et al (2010) found that employees seek advice from powerful, important, and socially influential individuals. Understanding the meanings of intra-organizational networks and utilizing the unfolded knowledge would contribute to overall management and individual career development.

2.2 The network science methods

Network science has rapidly emerged into an interdisciplinary field in the recent two decades after the two seminal works were published in the late 1990s (Sayama, 2015). One seminal work by Watts and Strogatz (1998) reflects that networks can be highly clustered yet simultaneously have small path lengths. The other seminal work by Barabási and Albert (1999) demonstrates that the degree distribution of large networks follows the power law, which features the scale-free nature of the network. The two seminal works develop an increasing number of literature in the field of network science, exploring structures, dynamics, and functions of various types of networks.

Among the enormous literature, a new trend of research is the study of multilayer networks, which feature understanding multiple layers of connectivity (Kivelä et al., 2014). It is necessary to understand the multiplexity of networks since it takes the same nodes with different edges into a single model for analysis. The current research utilizes several multilayer analysis methods, which will be discussed later in the paper.

2.3 Gap in the literature

Network studies in social science could use more advanced network science methods to answer relevant research questions. More research is needed to fill the gap between social science research topics and network science research methods. The current work is an example of utilizing advanced network science methods, specifically multilayer network methods, to study social science research questions.

3. Research Questions

1) What can managers learn from the intra-organizational networks to help with organizational management and strategic decision-making?
2) What can individual employees learn from the intra-organizational networks to help with learning and career success?

4. Data Source

The datasets we use are from a public index. It is retrieved from The Colorado Index of Complex Networks (ICON). The data file is called “Intra-organizational social networks”. Even though we use existing datasets, we are applying updated methods in our analysis. Multilayer network analysis has not been used towards these datasets, to our best knowledge. The basic information of the four networks, two multilayer networks each with two layers, are shown in Table 1.

Table 1. Basic information about the four intra-organizational networks

Network #	Name	Organization	Nodes	Edges
1	Advice requests	Consulting firm	46	879
2	Subjective value	Consulting firm	46	858
3	Advice requests	Research Team	77	2228
4	Skill awareness	Research Team	77	2326

Table 2. Meaning of edge and edge weights of the four intra-organizational networks

Network #	Survey Question (edge meaning)	Possible Answers (edge weights)
1	"Please indicate how often you have turned to this person for information or advice on work-related topics in the past three months"	0: I Do Not Know This Person; 1: Never; 2: Seldom; 3: Sometimes; 4: Often; and 5:Very Often
2	"For each person in the list below, please show how strongly you agree or disagree with the following statement: In general, this person has expertise in areas that are important in the kind of work I do."	0: I Do Not Know This Person; 1: Strongly Disagree; 2: Disagree; 3: Neutral; 4: Agree; and 5: Strongly Agree
3	"Please indicate the extent to which the people listed below provide you with information you use to accomplish your work"	0: I Do Not Know This Person/I Have Never Met this Person; 1: Very Infrequently; 2: Infrequently; 3: Somewhat Infrequently; 4: Somewhat Frequently; 5: Frequently; and 6: Very Frequently
4	"I understand this person's knowledge and skills. This does not necessarily mean that I have these skills or am knowledgeable in these domains but that I understand what skills this person has and domains they are knowledgeable in"	0: I Do Not Know This Person/I Have Never Met this Person; 1: Strongly Disagree; 2: Disagree; 3: Somewhat Disagree; 4: Somewhat Agree; 5: Agree; and 6: Strongly Agree

The consulting firm dataset contains information about the following employee attributes: the organizational level (1 Research Assistant; 2: Junior Consultant; 3: Senior Consultant; 4: Managing Consultant; 5: Partner), gender (1: male; 2: female), region (1: Europe; 2: USA), and location (1: Boston; 2: London; 3: Paris; 4: Rome; 5: Madrid; 6: Oslo; 7: Copenhagen).

Similarly, the employees in the research team have the following attributes: location (1: Paris; 2: Frankfurt; 3: Warsaw; 4: Geneva), tenure (1: 1-12 months; 2: 13-36 months; 3: 37-60 months; 4: 61+ months) and the organizational level (1: Global Dept. Manager; 2: Local Dept. Manager; 3: Project Leader; 4: Researcher). Table 2 presents the meanings of edges and the possible edge weights in each network.

5. Methodology and Results

5.1 Topological analysis

The following network statistics were used to measure the network features (as shown in Table 3).

1) Network Density: The ratio between the actual number of edges and the maximum possible number of edges in the network (Wasserman and Faust, 1994).
2) Average Shortest Path: refers to the average distance between any two nodes in the network (Bales and Johnson, 2006).
3) Transitivity: Transitivity measures the probability that the adjacent vertices of a vertex are connected. This is sometimes also called the clustering coefficient (Csardi, 2024).
4) Assortativity: measure of the extent to which vertices with the same properties connect to each other (Newman, 2002).
5) Out-degree: The number of edges going out of a vertex in a directed graph (Black, 2024).
6) In-degree: The number of edges coming into a vertex in a directed graph (Black, 2024).

Table 3. Network statistics

Network #	Density	Avg shortest path	Transitivity	Assortativity
1	0.425	1.493	0.578	-0.120
2	0.414	1.563	0.628	-0.038
3	0.381	1.605	0.567	-0.026
4	0.397	1.607	0.612	-0.021

Please note that assortativity here is all negative numbers, which indicates there are not enough hub nodes to maintain assortativity (Sayama, 2015).

Figures 1 to 8 are histograms showing the degree distributions of the four networks being studied. The degree distribution histograms are shaped like binomial and Poisson distributions. These indicate that the four networks being studied are somewhat formed by randomness (Barabási and Albert, 1999).

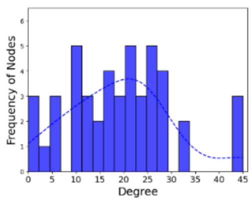

Figure 1. Network 1 Out-degree Distribution

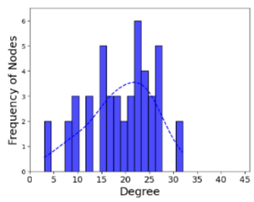

Figure 2. Network 1 In-degree Distribution

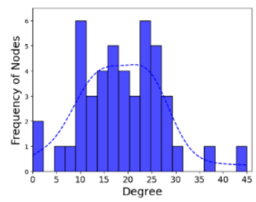

Figure 3. Network 2 Out-degree Distribution

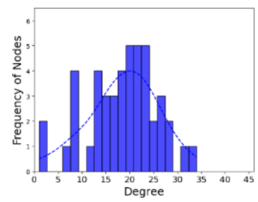

Figure 4. Network 2 In-degree Distribution

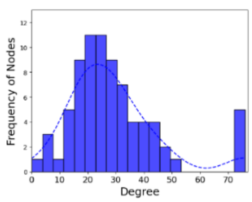

Figure 5. Network 3 Out-degree Distribution

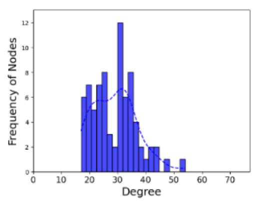

Figure 6. Network 3 In-degree Distribution

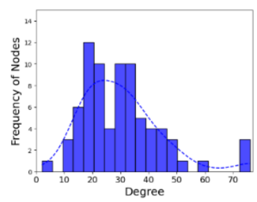

Figure 7. Network 4 Out-degree Distribution

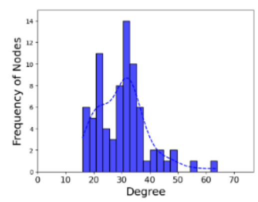

Figure 8. Network 4 In-degree Distribution

Tables 4 to 7 are aggregated results of out- and in-degree analysis by organizational levels. The results show that on average higher positions are associated with higher degrees, both out- and in- in all the four networks being studied.

Despite the average outcomes, surprisingly, individuals who have the highest degrees are not the ones who are in the highest positions. In network#1, nodes 12, 16, and 22 have the highest out-degree; this indicates that these three people usually ask for suggestions from other people more frequently. Nodes 2 and 20 have the highest in-degree, meaning these two people are the most valuable people to be asked for working suggestions. Identically, in network #2, nodes 20 and 22 have the highest out-degree, which indicates that these two people tend to think positively about their coworkers. Nodes 2 and 20 have the highest in-degree, which indicates that these two nodes obtained positive evaluations from their coworkers on their knowledge, skill, and ability. These nodes are all mid-level employees.

In network#3, nodes 15, 28, 49, 68 and 74 have the highest out-degree, which indicates that these people usually ask for suggestions from other people more frequently. Node 68 has the highest in-degree, which means that these two people are the most popular people to be asked for working suggestions. Identically, in network #4, nodes 15, 49, and 68 have the highest out-degree, which indicates that these people tend to think positively about their coworkers. Node 68 has the highest in-degree, which indicates that this node obtained positive evaluations from their coworkers on their knowledge, skill, and ability. Except for nodes 20 and 68, these nodes are all mid-level employees.

Table 4. Aggregated degree analysis by organization levels Network 1

orglevel	out_degree_mean	in_degree_mean
1	8.00	9.33
2	20.00	18.00
3	19.80	20.80
4	20.35	20.59
5	26.75	25.75

Table 5. Aggregated degree analysis by organization levels Network 2

orglevel	out_degree_mean	in_degree_mean
1	8.83	8.67
2	19.78	17.22
3	18.9	19.80
4	19.35	20.18
5	27.25	27.50

Table 6. Aggregated degree analysis by organization levels Network 3

orglevel	out_degree_mean	in_degree_mean
1	76.00	54.00
2	36.33	36.00
3	27.90	28.81
4	28.02	28.10

Table 7. Aggregated degree analysis by organization levels Network 4

orglevel	out_degree_mean	in_degree_mean
1	76	76.00
2	38	38.00
3	29.1	29.10
4	29.33	29.33

Table 8. Node number with highest out- and in-degree

Network #	Node number with highest out-degree	Node number with highest in-degree
1	node 12, 16, 22	node 2, 20
2	node 20, 22	node 2, 20
3	node 15, 28,49, 68, 74	node 68
4	node 15,49,68	node 68

5.2 Community detection

We applied the Louvain method (Lu et al., 2015) to detect communities within the four networks to see clustering patterns. A function called "best_partition" under Python community module with default parameters setting (partition=None, weight='weight', resolution=1.0, randomize=None, random_state=None) was applied for the community detection analysis. From the visualizations in Figures 9, 10, 11 and 12, we can see that network #1 has three communities, network #2 has two communities, network #3 has four communities, and network #4 has four communities.

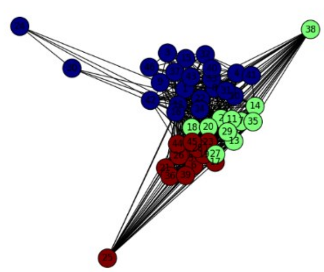

Figure 9.
Community Detection of Network #1

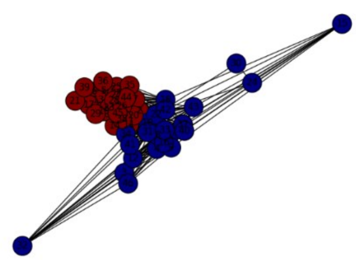

Figure 10.
Community Detection of Network #2

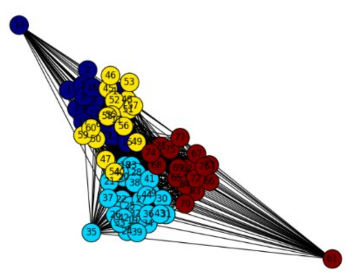

Figure 11.
Community Detection of Network #3

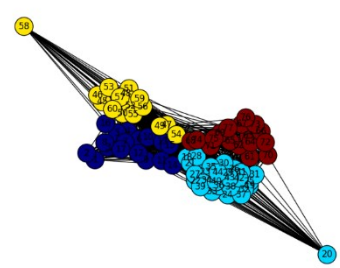

Figure 12.
Community Detection of Network #4

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Pearson correlation analysis between the attributes of community and nodes reflects the extent to which community formation is associated with individual employees' gender, region, location, organization level, and tenure.

The partition Pearson correlation is a statistical measure that assesses the linear relationship between two variables within each partition or group of data. This typically checks for linear relationships between data. The Sig. (2-tailed) value, or p-value, in the context of a Pearson correlation, indicates the probability that the observed correlation occurred by chance. A lower p-value suggests that the observed correlation is statistically significant, meaning it is unlikely to have occurred by random chance. A two-tailed test considers the possibility of the correlation being either positive or negative. The analysis of this work was through SPSS Pearson correlation analysis.

From the correlation analysis outputs, region, and location are important associated variables for the community. In network #1, the community is significantly correlated with the region (coefficient of 0.830) and location (coefficient of -0.695). In network #2, the community is primarily correlated also with the region (coefficient of 0.877) and location (coefficient of -0.735). In network #3, the community is totally correlated with the region (coefficient of 1.000). In network #4, the community is mainly correlated with the region (coefficient of 0.802).

In networks #3 and #4, tenure is also a significant influencing variable for the community (coefficient of 0.354 and 0.308).

Table 9. Correlation analysis of Network #1. The p-value annotation legend is as follows. **: 0.001 < p <= 0.01.

		gender	region	location	orglevel	partition
partition	Pearson Correlation	.009	.830**	-.695**	.167	1
	Sig. (2-tailed)	.952	.000	.000	.268	
	N	46	46	46	46	46

Table 10. Correlation analysis of Network #2. The p-value annotation legend is as follows. **: 0.001 < p <= 0.01.

		gender	region	location	orglevel	partition
partition	Pearson Correlation	.051	.877**	-.735**	.146	1
	Sig. (2-tailed)	.737	.000	.000	.334	
	N	46	46	46	46	46

Table 11. Correlation analysis of Network #3. The p-value annotation legend is as follows. **: 0.001 < p <= 0.01.

		orglevel	location	tenure	partition
partition	Pearson Correlation	-.061	1.000**	.354**	1
	Sig. (2-tailed)	.597	.000	.002	
	N	77	77	77	77

Table 12. Correlation analysis of Network #4. The p-value annotation legend is as follows. **: 0.001 < p <= 0.01.

		orglevel	location	tenure	partition
partition	Pearson Correlation	-.042	.802**	.308**	1
	Sig. (2-tailed)	.715	.000	.006	
	N	77	77	77	77

5.3 Maximal clique detection

A clique in a graph is a set of vertices where every pair of distinct vertices is connected by an edge. A maximal clique (Makino and Uno, 2004) in a graph is a clique that cannot be extended by adding an adjacent vertex.

Let G = (V, E) be a graph, where V is the set of vertices and E is the set of edges. A subset $C \subseteq V$ is a clique in G if, for every pair of distinct vertices u, v in C, there is an edge (u, v) in E.

A clique C is a maximal clique in G if C is a clique, and there is no vertex w in V such that $C \cup \{w\}$ is a clique in G. In other words, a maximal clique cannot be extended by adding an adjacent vertex.

Applying this analysis to the four networks, we get the maximal cliques shown in Figure 13. From the discovered maximal cliques, we notice that the highest centrality nodes (Nodes with the highest out- and in-degree) are represented in the maximal cliques. This could be due to the fact that the most influential individuals are part of a clique that connects to the greatest number of employees due to the hierarchical nature of the organization. However, we must emphasize that this type of maximal clique formation can happen without any hierarchy due to the influence of certain individuals in the network.

The large size of the maximal cliques also indicates the resilience of the organizations. Larger maximal cliques act to stabilize the network under node or edge removal. So, even if some employees left the organization, the core group could still function resiliently.

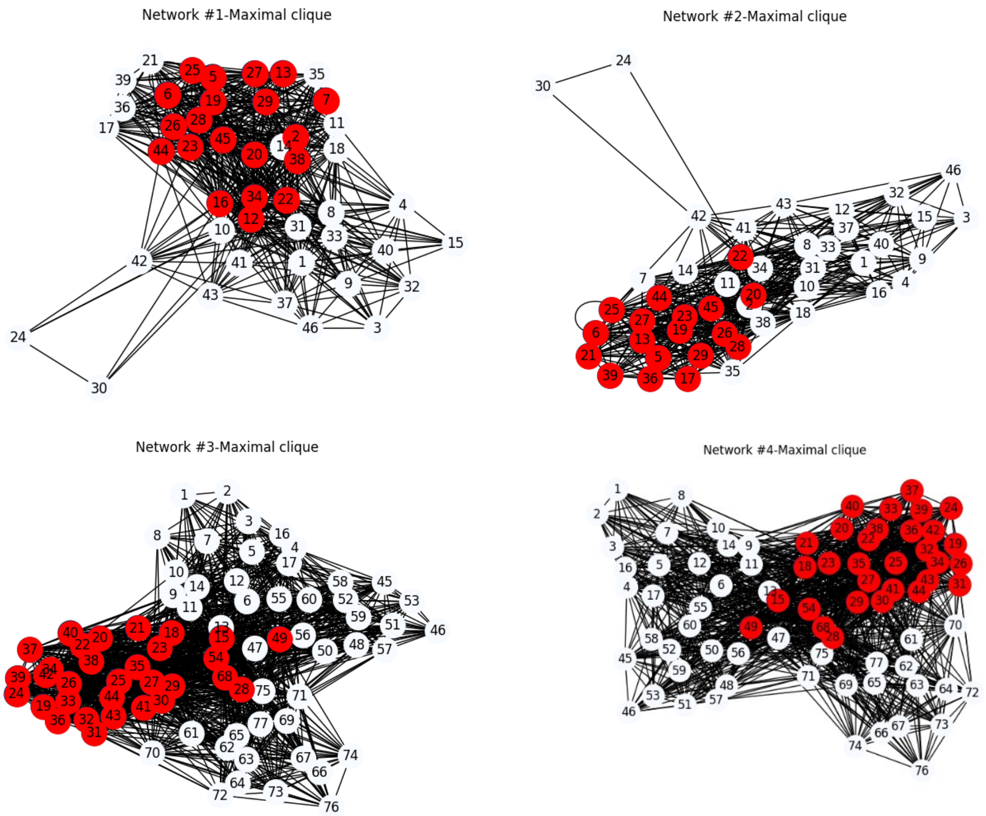


Figure 13: Maximal cliques for each of the four networks

5.4 Multilayer analysis

From the topological analysis, we can see that though the four networks describe different relationships between employees in two organizations, different layers of the same organization still have strong correlations and similarities in the topological construction. In order to find out more interesting phenomena, we create two multilayer network models to analyze the relationship between the two layers of each of the two organizations. Multilayer network analysis is a cutting-edge method in network science. In this section, we primarily present the results of a multilayer analysis of the two consulting firm networks (networks #1 and #2).

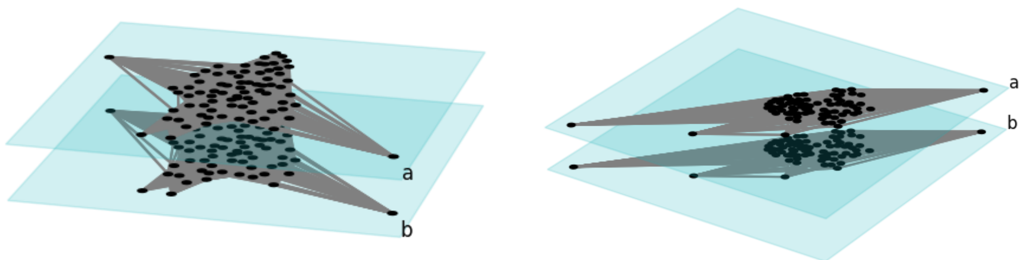


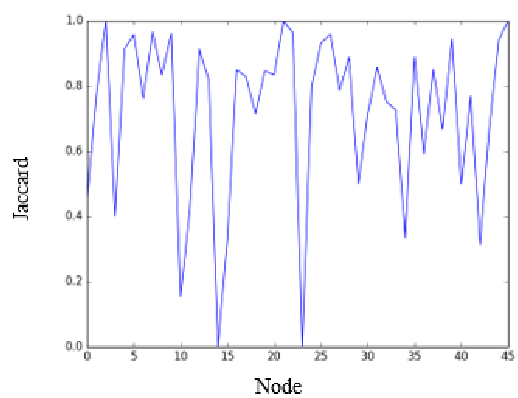
Figure 14. Multilayer Visualization (Left: Network #1 and #2; Right: Network #3 and #4)

5.5 Jaccard similarity analysis

We examine the similarity of the two layers by calculating the Jaccard index on the node level. General Jaccard similarity (Real and Vargas, 1996) is a popular method to examine the degree of similarity between sets. It is also known as the Tanimoto coefficient. The formula is as follows:

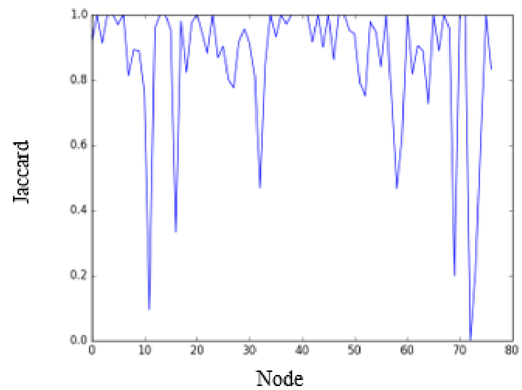
$$\mathrm{Jaccard}(\mathrm{A}, \mathrm{B}) = (\mathrm{A} \cap \mathrm{B})/(\mathrm{A} \cup \mathrm{B})$$

A and B represent the two sets. Here we use $N_i(j)$ to represent the neighbor set of node j in network. We calculate $Jaccard(\mathrm{N}_1(i), N_2(i))$ and $Jaccard(\mathrm{N}_3(i), N_4(i))$ to see the similarities of two layers on node level. This specific calculation helps in understanding the overlap between these sets, often used in network analysis to study the connectivity and overlap of nodes.



$$E[Jaccard(\mathrm{N}_1(i), N_2(i))] = 0.7191$$

Figure 15. Similarity analysis Network #1 and #2



$E\left[Jaccard\left(N_3(i), N_4(i)\right)\right] = 0.8578$

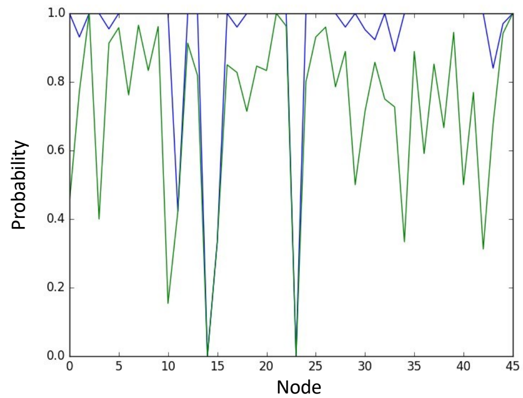
Figure 16. Similarity analysis Network #3 and #4

From the Jaccard index plots and the average values, we can see that both the consulting firm and the research team are similar in the two layers of networks representing different relationships. The high similarity means that employees know who the valuable connections are to request advice from. Meanwhile, the similarity index of the research team is higher than that of the consulting firm.

5.6 Difference analysis

After calculating the Jaccard index, we can see the two layers of consulting firm networks are similar to each other. But there are also some differences between these two layers. The differences consist of two parts. The first part comes from the situation that some people know others' abilities but never ask questions to them. The other part means they ask questions to some of their connections but know nothing about their expertise. The latter situation tends to affect the work efficiency. So we calculate $P(N_2(i)/N_1(i))$ to observe the proportion of the second situation that is counted for in the difference.

Figure 17 shows the distribution of $P(N_2(i)/N_1(i))$ on node level. There are two nodes who have no neighbor in network 1, which means they have never asked questions to others. So their probability shows as 0. To avoid their influences, we delete these two nodes and get the average probability, which is 0.9152. It means that about 9 percent of advice was sought from individuals who do not know what their expertise is. There are also some special points in this distribution. Node 14, 23 asks no questions. Node 11 doesn't know who he/she should ask. He/she always asks questions to those he/she knows nothing about their expertise. As another example, node 10 knows a lot of people's abilities and always knows who he/she should seek advice from.



$$E[P(N_2(i)/N_1(i))] = 0.9152$$

Figure 17. Difference analysis between network #1 and #2

5.7 "Bad edge" analysis

In the earlier analysis, we find most people in this consulting firm know who they should ask questions for and seek advice from. However, according to the weights of the second network, we know that not all the employees are satisfied with their colleagues. Sometimes, they have to ask for advice from someone who is not very professional in their mind. In the set $N_1(i) \cap N_2(i)$, we calculate a specific probability which reflects what we call as "bad edge". We are interested in finding out how many edges exist that are weighted more than the median, with nodes that are seen as not as valuable (advice request edge weight >= 3 & subjective value <=3). We collect the total number of bad edges of each node.

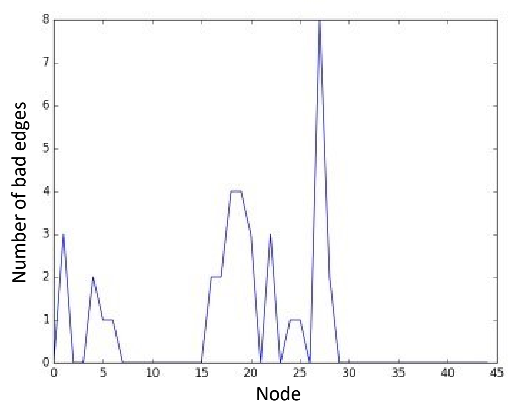


Figure 18. "Bad edge" distribution of Network #1 and #2

We get the $average(bad\ edge) = 0.7074$ and $sum(bad\ edge) = 33$. This result shows that on average each individual has 0.7 "bad edge" and the organization has 33 "bad edges" exist in total. We also find out a special node 27, who always requests advice from those he/she thinks are not that professional.

5.8 Node ranking in monoplex network

To further analyze the system with multiplexity, we generate a monoplex network by combining the weights and structures from the two layers of the consulting firm. We delete some 'noisy' data to avoid the influence of inter-layer differences. In other words, we only use $N_1(i) \cap N_2(i)$ as the new neighbor sets. We analyze the new monoplex network specifically to rank nodes. By doing this, we are able to see who the most important individuals are in the firm.

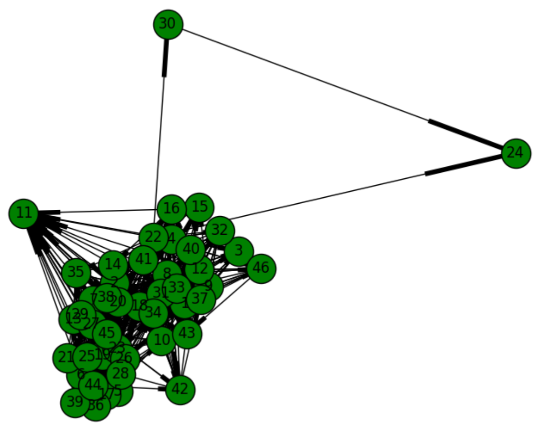


Figure 19. Monoplex Network Visualization

The new weight of node i is defined as follows:

$$Weight(i) = \sum_{i=1}^{46}\sum_{j=1}^{46}(weight_1(i,j) * weight_2(i,j))$$

$weight_1(i,j)$ and $weight_2(i,j)$ mean the weight value in Network 1 and Network 2.

Then, we can get the new weight rank, which represents their contributions to the company. For the top five employees, we can see their organization levels are all from 4 to 5.

We also conduct a correlation analysis to confirm the relationship between organization level and node rank. This outcome shown in Tables 13 and 14 implies that contribution ranking is related to organization levels.

Table 13. Top 5 nodes in monoplex network analysis

Node ID	Gender	Org-Level	Weight	Rank
45	1	5	249.625	1
8	1	5	239.0156	2
2	1	4	233.7344	3
20	1	5	217.6875	4
26	1	4	206.5938	5

Table 14. Correlation analysis between node rank and attributes. The p-value annotation legend is as follows. *: 0.01 < p <= 0.05, **: 0.001 < p <= 0.01.

		gender	orglevel	location	region	weight	Rank
rank	Pearson Correlation	.340*	-.611**	.418**	-.367*	-.971**	1
	Sig. (2-tailed)	.021	.000	.004	.012	.000	
	N	46	46	46	46	46	46

6. Findings and Conclusion

Using the analysis outcomes, we aim to answer our research questions from two levels: organizational and individual employee levels. On the organizational level, we would like to make recommendations to the organization managers on how they could utilize the findings to make strategic managerial decisions. On the individual level, we would like to inform employees on ways to utilize the networks for their career development and success.

Finding #1. Both the consulting firm and the research team are tightly connected networks.
Finding #2. The consulting firm could do better in promoting mutual understanding among their employees to increase work efficiency.
Finding #3: Region and location are significantly correlated with communications.
Finding #4: Higher organization level is associated with higher out- and in-degree.
Finding #5: Key nodes in intra-organizational networks are mid-level employees.
Finding #6: Not all advice-seeking relations are as valuable. “Bad edges” exist.

6.1 Recommendations for managers

Recommendation #1: Invest in knowledge-sharing procedures within organizations, such as building an expertise database which stores every

employee's skill and knowledge as references for the entire firm, and providing seminar/workshop/presentation opportunities for employees to exchange ideas.
Recommendation #2: Promote inter-region communication opportunities.
Recommendation #3: Use intra-organizational networks as tools to understand employees' contributions and importance.

6.2 Recommendations for individual employees

Recommendation #4: Evaluate your relationships with coworkers and their trustworthiness before seeking advice from them.
Recommendation #5: Do not isolate yourselves in your workplace and try to communicate more with coworkers regardless of work- or non-work-related information sharing.
Recommendation #6: Identify the information hub person in your organization and utilize his or her knowledge.

7. Limitations

This paper is based on self-reported data, which may contain errors and biases compared with objective circumstances. In the meantime, our networks are limited in terms of their sizes. N1 and N2 contain 46 nodes, while N3 and N4 contain 77 nodes. The datasets are also publicly accessible data that may be used by other researchers.

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