Multigraph Approach to Social Network Analysis

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Introduction

In life, every individual is connected to other people and every individual is part of a social network. The positions and roles of the individuals, vary greatly and an individual simultaneously can be a member of many networks. Based on empirical survey data among members of a defined community (i.e. academic staff of a given Faculty), we constructed four distinct informal networks (informal collaboration, friendship, opinion leadership and social capital networks). Subgroups within the community were detected by the strength of relationships between people.

The data set

The social network of a Faculty of a UK university was studied. Ties between individuals were characterised according to four types of tie strengths (personal friendship, informal professional ties, social capital, opinion leadership) via online questionnaire. The tie strength measures were developed prior to data collection using an independent sample of university students (n = 173). Cronbach's α was greater than 0.8 for all measures (0.81 for opinion leadership, 0.84 for social capital and 0.91 for personal and professional tie strengths).

Graph representation

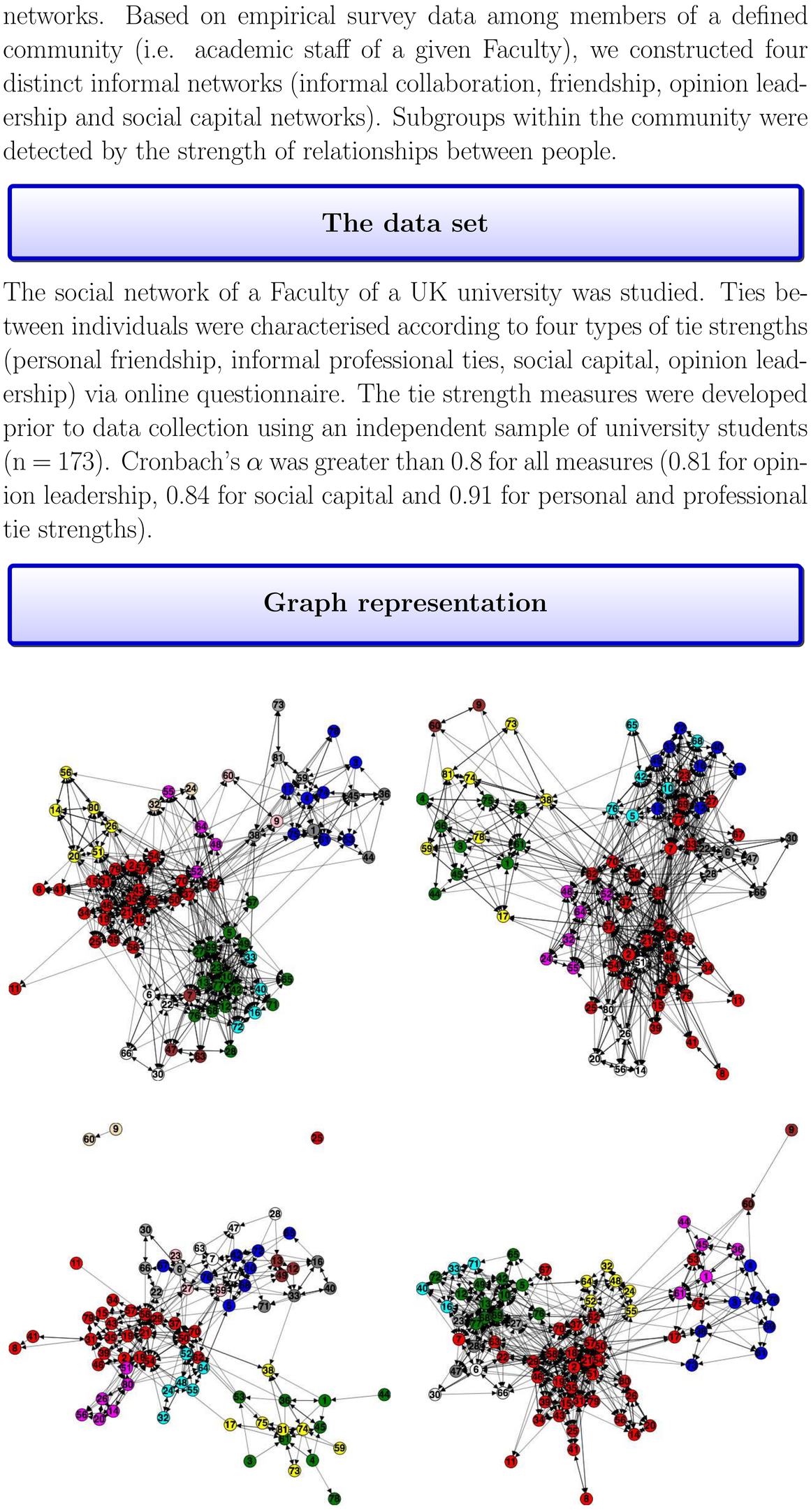

Figure 1: Graph representation of the different aspects of the studied social network. Edge colors represent tie strength, node colors represent identified communities. Upper left: personal friendship (PERS) network, upper right: informal professional (PROF) network, lower left: opinion leadership (OL) network, lower right: social capital (SC) network

The Markov Clustering Algorithm [1] was used to identify communities. Other "classical" algorithms were unsuitable mostly because of their inability to handle directed graphs.

Correlations between the networks

Several centrality scores have been calculated for each of the nodes in the network (including: betweenness, closeness, eccentricity, node degree and PageRank), and the centrality score correlations have been calculated between pairs of networks. Results show that although there is positive correlation between the networks, each networks grabs a different aspect of social relationship between individuals. Significant correlation was observed between the SC, PROF and OL graphs, while the centralities of PERS were only correlated to the centralitie of PROF. As a reference, the organizational structure graph (STR) has also been included in the comparison.

	SC	STR	PERS	PROF
OL	**0.4928**	0.3433	0.4137	**0.5228**
SC	-	0.4117	0.4410	**0.5704**
STR	-	-	0.3191	0.3944
PERS	-	-	-	**0.5046**

	SC	STR	PERS	PROF
OL	**0.5385**	0.4147	0.5144	**0.5586**
SC	-	0.4702	0.4862	**0.6667**
STR	-	-	0.4509	0.4888
PERS	-	-	-	**0.5981**

Figure 2: Kendall correlations of betweenness (left) and closeness (right) centrality scores between networks. Bold typeface denotes significant correlation.

Demographical properties of the clusters

We used contingency tables and Fisher's exact test to evaluate the inner demographical composition of the clusters. Results show that all clusters are homogenous with respect to all examined demographical properties (age, gender, seniority) except school affiliation. In other words, individuals tend to group together based on their school affiliation and not by any other qualitative characteristics. This suggests that organisational structure determines social structure to an extent greater than the demographical properties of the participants.

Social capital brokers and opinion leaders

To test Burt's assumption about opinion leaders and social capital brokers [2], we ordered nodes according to the sum of their incoming edges in the SC and OL networks. Nodes with the 20 highest incoming SC and OL edge weight sums are shown in decreasing order here:

OL	**54**	**50**	**31**	**21**	**58**	**7**	48	**42**	**69**	**77**	**70**	**35**	26	27	10	16	64	**68**	**29**	61
SC	**58**	**54**	**69**	**31**	**29**	**21**	**77**	**68**	**42**	18	**50**	**7**	51	19	**70**	62	2	57	**35**	46

Figure 3: Nodes with the 20 highest incoming SC and OL edge weight sums in decreasing order. Overlaps are marked with bold typeface.

Note that there is an overlap of 65% in the two lists above, suggesting that opinion leaders (nodes with many incoming OL edges) and social capital brokers (nodes with many incoming SC edges) are usually the same. This is supported further by the Spearman correlation of 0.8147 between the incoming SC and OL edge weight sums.

Acknowledgements

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References

[1] Stijn van Dongen. *A stochastic uncoupling process for graphs.* Technical Report INS-R0011, National Research Institute for Mathematics and Computer Science in the Netherlands, Amsterdam, May 2000.

[2] Ronald S. Burt. *The Social Capital of Opinion Leaders.* The Annals of the American Academy of Political and Social Science, **556**(1):37–54, 1999.