# *Academics’ online connections: Characterising the structure of personal networks on academic social networking sites and Twitter*

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## Abstract

Academic social networking sites (SNS), such as Academia.edu and ResearchGate, seek to bring the benefits of online social networking to academics’ professional lives. Online academic social networking offers the potential to revolutionise academic publishing, foster novel collaborations, and empower academics to develop their professional identities online. However, the role that such sites play in relation to academic practice and other social media is not well understood at present.

Arguably, the defining characteristic of academic social networking sites is the connections formed between profiles (in contrast to the traditional static academic homepage, for example). The social network of connections fostered by SNSs occupies an interesting space in relation to online identity, being both an attribute of an individual and shaped by the social context they are embedded within. As such, personal network structures may reflect an expression of identity (as “public displays of connection” (Donath & boyd, 2004) or “relational self portraits[s]” (Hogan & Wellman, 2014)), while social capital has been linked to network structures (Crossley et al., 2015). Network structure may therefore have implications for the types of roles that a network can play in professional life. What types of network structures are being fostered by academic SNS and how do they relate to academics’ development of an online identity?

This presentation will discuss findings from a project which has used a mixed-methods social network analysis approach to analyse academics’ personal networks online. The personal networks of 55 academics (sampled from survey participants, to reflect a range of disciplines and job positions) on both one academic SNS (either Academia.edu or ResearchGate) and Twitter were collected and analysed. Differences in network structure emerged according to platform, with Twitter networks being larger and less dense, while academic SNS networks were smaller and more highly clustered. There were differences between academic SNS and Twitter in the brokerage positions occupied by the participant. The results are discussed in relation to other salient studies relating network structure in online social networks to social capital, and implications for academic practice. Future work, including co-interpretive interviews to explore the significance of network structures with participants, is introduced.

# 1. Introduction

Social networking sites (SNS) represent a particular type of social media, which rather than focusing upon user-generated content (such as videos or photographs) foregrounds the user, through their profile and social connections (boyd & Ellison, 2007). The use of social media and social networking sites has become a mainstay of internet and World Wide Web use for many (Rainie & Wellman, 2012), and academia is no exception. In recent years, a slew of platforms (which will be referred to as academic SNS) have sought to bring online social networking to academics, the largest sites being Academia.edu and ResearchGate. Features of academic SNS are based on themes of enhancing collaboration, scholarly communication and digital identity management for academics (Bullinger et al., 2010; Espinoza Vasquez & Bastidas, 2015). A fundamental characteristic of academic SNS is the network of social connections formed between profiles (in contrast to the traditional academic homepage), although the network is not easily visualised or navigated in academic SNS at present.



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The structures of networks fostered by sites may have important implications for the types of uses and interactions that can be realised through them; for example, studies of social media network structures in other contexts have shown links between network structure and social capital (Brooks et al., 2014; Ellison et al., 2014). In the context of networked learning, the creation of these types of online networks, and the interactions facilitated by them, represent a form of "networked professional learning" and a better understanding of the structure and composition of such networks is an open research question for the field (de Laat & Strijbos, 2014). While forms of computer-mediated communication (such as SNS) are often linked to definitions of networked learning, an individuals' learning network may span a range of different tools. As such, this study focuses on two of the main types of social media platform used by academics in their professional life; academic SNS, and Twitter. While academic SNS are specifically designed for academics, their role is viewed by many users as passive online business cards, while more actvie functions such as discussions take place on Twitter (Van Noorden, 2014).

This paper represents part of a larger doctoral research project which has taken a mixed methods social network analysis approach (Dominguez & Hollstein, 2014) to explore the role and structure of academics' professional use of online SNS (Jordan, 2014a). The personal networks of 55 UK-based academics were sampled, from both an academic SNS (either Academia.edu or ResearchGate, depending on which they use) and Twitter, to explore whether differences in network structure exist according to different platforms. As a pilot study showed differences in the structure of the network of Open University-affiliated academics on academic SNS according to job position and subject area (Jordan, 2014b), the sample was constructed to reflect these factors. In this paper, the results of the network analyses will be described. Implications of the networks' structural characteristics will be discussed, and future work introduced.

## 2. Methods and data collection

The initial phase of the project comprised an online survey, which served to gather a baseline of opinions about the ways which academics use online social networks, and also to recruit participants for further follow-up activities including network analysis. The survey ran from 19th November 2014 to 3rd February 2015, during which time a total of 528 responses were received. To ensure that a range of different perspectives were included, a purposive sampling approach (Arber, 2001; Teddlie & Yu, 2007) was taken when selecting participants for network analysis from the pool of survey respondents who indicated a willingness to take part. Initially, the following criteria were applied: those who use Twitter and an academic SNS (either Academia.edu or ResearchGate), and are based in the UK (to allow for follow-up interviews). Sampling was also stratified to ensure representation across three disciplinary areas (Arts & Humanities, Natural Sciences and Social Sciences) and job positions (PhD students, researchers, lecturers and professors). A total of 55 academics were included in the sample on this basis.

For each participant, personal networks from one academic SNS and from Twitter were collected. Personal networks are defined as the participant, their followers and those they are following, and any connections that exist between them (Molina, Maya-Jariego & McCarty, 2014). Web scraping software was used to collect data from Academia.edu, while ResearchGate data was collected by the researcher (in keeping with their Terms of Service). Twitter data collection was carried out in an automated fashion using the Twitter API via NodeXL (Smith et al., 2009). However, Twitter places restrictions on the amount of information that can be collected via its API (full data cannot be collected if followers or following >2000), so full Twitter networks could not be collected for eight of the participants. Once collected, the network data was imported into social network analysis software packages (Gephi and Pajek) for visualisation and analysis (Bastian, Heymann & Jacomy, 2009; De Nooy, Mrvar & Batagelj, 2005).

A limitation of this study may reflect the way that participants were recruited. While the online survey was publicised by the researcher on a number of social media platforms, circulation was most extensive via Twitter, where the information enjoyed a high level of retweeting. As a result, the sample may be biased towards academics with larger Twitter networks. The study still provides a novel contribution to understanding academics' use of social media, although the results may not be generalisable to academia as a whole. As the platforms are public, academics could be targeted to create a sample of those with small Twitter networks and who use academic SNS. Ethically, however, it was more in keeping with the ethos of the project for participants to opt-in to network analysis, and the survey was a necessary vehicle to facilitate this.

# 3. Results and analysis

## 3.1 Network size

Metrics concerned with network size included the number of people (nodes) in networks, and the number of communities (as identified by the modularity algorithm in Gephi; Blondel et al., 2008). Descriptive statistics for the number of nodes and communities are shown in Table 3.1.1.

Table 3.1.1: Descriptive statistics for network size.

| | | N | Minimum | Maximum | Mean | St. dev. |
|---|---|---|---|---|---|---|
| Number of nodes | Academic SNS | 55 | 10 | 2173 | 154.95 | 293.13 |
| | Twitter | 47 | 19 | 2480 | 914.57 | 613.00 |
| Number of communities | Academic SNS | 55 | 1 | 8 | 4.29 | 1.26 |
| | Twitter | 47 | 3 | 8 | 4.79 | 1.06 |

Considering network size in terms of number of nodes; the range of personal network sizes observed is similar across SNS and twitter, although the average is much larger for Twitter. The difference between each individual's academic SNS and Twitter personal network is statistically significant (paired t-test; there was a significant difference in number of nodes in Academic SNS (M=155.94, SD=316.70) and Twitter (M=914.57, SD=613.00) personal networks; $t(46)=-8.626$, $p<0.05$). There is a significant correlation between size of networks on both platforms; regression analysis showed that the number of nodes in academic SNS personal networks is significantly predicted by the number of nodes in Twitter personal networks ($R2=0.084$, $p=0.048$). The low R2 of this finding indicates that only a small proportion of the variation in network size for SNS is predicted by Twitter network size.

There were no significant differences in network size overall (nodes) on either platform according to job position or discipline. However, as both the academic SNS and Twitter networks are directed relationships, it is also possible to consider nodes in terms of in-degree and out-degree (the number of followers, and the number of people an academic is following, respectively). Significant differences in in-degree on academic SNS were found according to job position (independent samples Kruskal-Wallis test, $\chi2(3, N=55)=11.843$, $p=.008$); PhD students show the lowest in-degree, with professors the highest (figure 3.1.1). Neither Twitter in-degree nor out-degree showed differences according to job position.

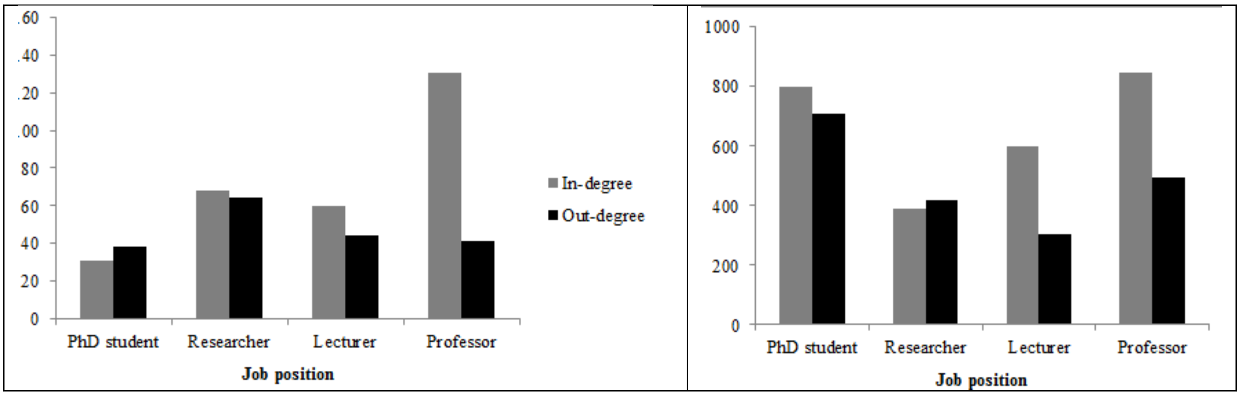

Figure 3.1.1: Median average in-degree (grey bars) and out-degree (black bars) of personal networks on academic SNS (left) and Twitter (right), according to job position (n=55).

Considering network size in terms of number of communities detected within the networks, Twitter networks comprise a greater number of average communities (Table 3.1.1), with academics' Twitter networks exhibiting significantly more communities than their academic SNS (paired t-test; there was a significant difference in number of communities in Academic SNS (M=4.28, SD=1.330) and Twitter (M=4.79, SD=1.062) personal networks; $t(46)=-2.226$, $p=0.031$). However, there is not a significant correlation between the two; so it does not


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follow that those with more communities on one platform, have more communities on the other. No significant differences in number of communities were found according to job or discipline on either site.

### 3.2 Network structure

Network structure was explored via five metrics (Borgatti et al., 2013; DeJordy & Halgin, 2008; Prell, 2012):
- Network density; the proportion of all possible network connections that have actually been made.
- Clustering; the proportion of all triplets (groups of three nodes with two or three connections) that are all connected (i.e. have three connections, the maximum possible between any three nodes).
- Reciprocity; the proportion of all network connections that have been made mutually (i.e. connections exist in both directions between a pair of nodes).
- Betweenness centrality; the proportion of shortest paths (between every possible pair of nodes in the network) that include the participant.
- Brokerage roles; a series of descriptions of how the participant relates to connections within and between communities in the network

With the exception of brokerage roles, the metrics are summarised in Table 3.2.1.

Table 3.2.1: Descriptive statistics for network structure.

| | | N | Minimum | Maximum | Mean | St. dev. |
|---|---|---|---|---|---|---|
| Density | Academic SNS | 55 | 0.01 | 0.27 | 0.08 | 0.06 |
| | Twitter | 47 | 0.01 | 0.25 | 0.05 | 0.04 |
| Reciprocity | Academic SNS | 55 | 0.00 | 0.86 | 0.41 | 0.13 |
| | Twitter | 47 | 0.00 | 1.00 | 0.36 | 0.08 |
| Betweenness centrality | Academic SNS | 55 | 0.00 | 0.72 | 0.46 | 0.17 |
| | Twitter | 47 | 0.14 | 0.74 | 0.43 | 0.13 |
| Clustering coefficient | Academic SNS | 55 | 0.27 | 0.58 | 0.41 | 0.08 |
| | Twitter | 47 | 0.24 | 0.46 | 0.34 | 0.05 |

Participants personal networks on academic SNS are significantly more dense than their Twitter networks (paired t-test; there was a significant difference in network density in Academic SNS (M=0.09, SD=0.01) and Twitter (M=0.05, SD=0.01) personal networks; t(46)=-3.441, p=0.001). No correlation was found between density of networks across both platforms, and no significant differences in density on either platform were found in relation to discipline or job position.

The extent of clustering was found to be significantly higher in academic SNS than Twitter personal networks (paired t-test; there was a significant difference in clustering coefficient in Academic SNS (M=0.41, SD=0.08) and Twitter (M=0.34, SD=0.05) personal networks; t(46)=-5.191, p<0.05). The only significant difference on demographics was found on academic SNS according to job position (independent samples median test. $\chi$2(3, N=55)=7.848, median=0.426, p=.049), with professors showing much lower clustering compared to other groups.

Reciprocity was significantly higher in academic SNS than Twitter networks (paired t-test; there was a significant difference in reciprocity in Academic SNS (M=0.41, SD=0.02) and Twitter (M=0.36, SD=0.01) personal networks; t(46)=-2.269, p=0.028). Contrasting differences according to demographic characteristics of participants were found on different platforms. Academic SNS showed no significant differences in reciprocity according to job position, but did according to discipline (independent samples Kruskal-Wallis test, $\chi$2(2, N=55)=8.049, p=.018), with higher levels of reciprocity observed in Arts & Humanities than Natural or Social Sciences. Twitter also exhibited this trend in disciplines, although not to a statistically significant extent. Significant differences in reciprocity in Twitter networks were found in relation to job position (independent samples Kruskal-Wallis test, $\chi$2(3, N=47)=8.087, p=.044), with PhD students showing highest reciprocity and professors the lowest.

Two metrics were used to explore the extent and nature of brokerage exhibited by participants in their networks (Burt, 2005). In the context of personal networks, betweenness centrality can be used as a proxy for the extent of structural holes and hence brokerage being performed by ego (the participant); a higher betweenness centrality would indicate that a greater proportion of shortest paths between any two nodes in the network need to pass through ego, thereby acting as a broker between nodes that would not otherwise be connected (Prell, 2012).

Normalised betweenness centrality was used for comparability, although it was broadly consistent across platforms and did not show differences according to discipline or job position

Brokerage was also examined using Pajek to calculate Gould and Fernandez' brokerage roles for each participant and platform (De Nooy, Mrvar & Batagelj, 2005). Gould and Fernandez characterised five types of brokerage role based on the position of ego relative to other communities in the network (figure 3.2.1). As the figures generated depend on the size of an academics' network, the modal brokerage category was recorded for each academic on each site. A divide in the relative frequency of brokerage roles was found according to site (figure 3.2.2).

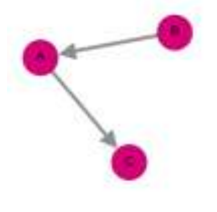
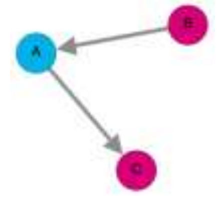
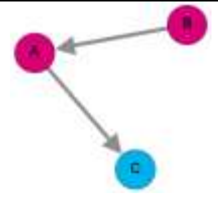
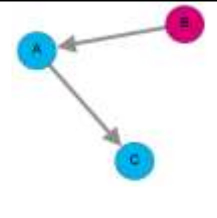
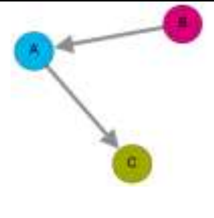
| Coordinator | Itinerant broker | Representative | Gatekeeper | Liaison |
|---|---|---|---|---|
|  |  |  |  |  |
| Broker is part of a community and mediates between other members of the same community | Broker mediates between members of the same community without being a member herself. | Broker mediates flow of information out of a community. | Broker mediates flow of information into a community. | Broker mediates between two different groups, neither of which she belongs to. |

Figure 3.2.1: Types of brokerage roles identified by Gould and Fernandez. Node ‘A’ is the broker in each; nodes are colour-coded according to membership of different communities. After de Nooy et al. (2005), Prell (2012).

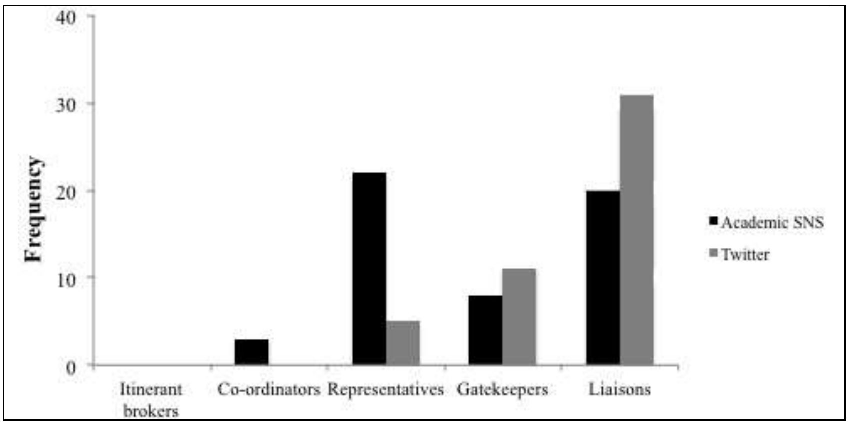


Figure 3.2.2: Frequency of modal brokerage types for personal networks on academic SNS and Twitter.

# 4. Conclusions and future work

This work has provided an insight into the social networks cultivated by academics on two contrasting social media platforms which are used in their professional lives. First, substantial differences in structure of personal networks are observed according to different platforms (academic SNS compared to Twitter); and second, some aspects of personal network structure show differences according to academics' job position or discipline.

Trends in the data show that academics' personal networks developed on academic SNS are smaller, more dense, more highly clustered around discrete communities and show greater reciprocity. In contrast, Twitter networks are larger and more diffuse. The differences are illustrated by the example of the personal networks of an academic whose academic SNS and Twitter networks were closest to median rank in terms of network size (number of nodes) across both platforms, in figure 4.1. Although no significant differences were found in betweenness centrality on different platforms, the types of brokerage role performed by ego is contrasted on different sites, with academics most frequently being 'liaisons' on Twitter, and 'representatives' on academic SNS. The trends in network structure suggest that academic SNS may preserve offline relationships and existing academic hierarchies to a greater extent than Twitter.

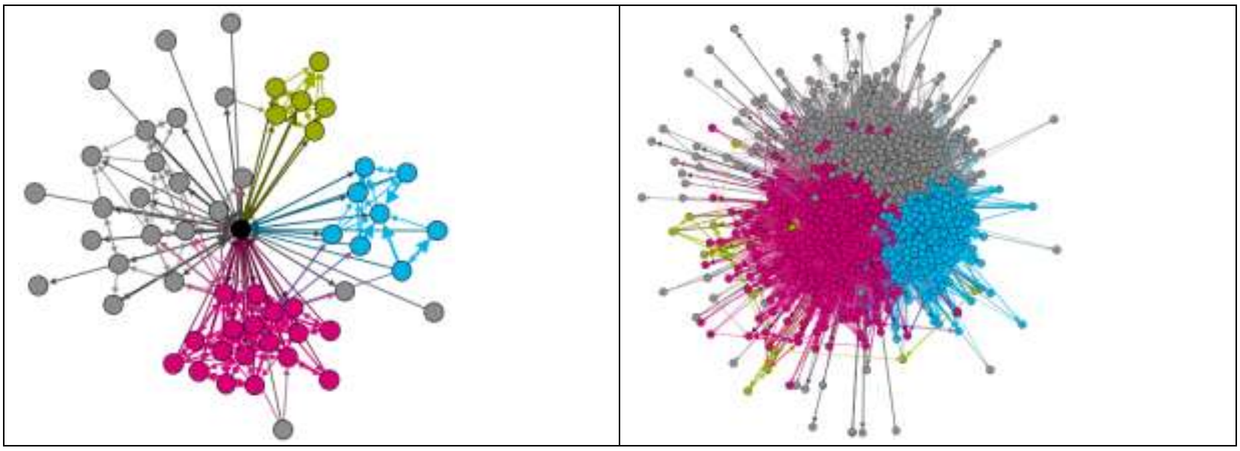


Figure 4.1: Personal networks of an Arts & Humanities lecturer whose personal networks on both platforms are approximately average size overall (left, Academia.edu, ranked 21st; right, Twitter, ranked 27th).

While the differences in structure according to different platforms are observed throughout the analysis, the study also found some more nuanced but significant differences in network structure according to personal characteristics of participants, such as job position and subject area. Although the overall size of networks did not vary, significant differences were found in terms of job position when considering the direction of relationships. The differences also support the notion that academic SNS are preserving academic hierarchies to a greater extent than Twitter. On both types of platform, professors show the highest average number of followers, and the largest disparity with the number of people that they choose to follow. In stark contrast, while PhD students have the fewest average number of followers and following on academic SNS, they follow the most on Twitter, and have second highest average number of followers after professors. Researchers and lecturers show intermediate levels of followers and following on both platforms, with lecturers exhibiting a greater number of followers than following on average compared to researchers on both platforms.

Two further metrics showed significant differences according to demographic characteristics. In the context of academic SNS, professors' networks showed significantly lower clustering compared to other job positions. Given the dramatic difference in terms of followers and following observed for professors on academic SNS, the lower clustering could be explained by having a much greater proportion of members of the network who are following due to their fame or reputation, who do not know other members of the network. The extent of reciprocity observed varied according to platform, job position and discipline. Reciprocity was higher in academic SNS than Twitter networks; that is, if an academic follows someone, they are more likely to also be followed back. For Twitter, PhD students' networks showed the highest level of reciprocity, and professors the lowest. On both types of platform, networks of academics from the Arts and Humanities showed the greatest levels of reciprocity compared to other disciplines (significantly higher in the context of academic SNS).

The results help illuminate the role that online social networks may play in relation to networked professional learning. The contrasting features of the networks on different platforms imply different relationships and modes of learning according to different types of site. While both academic SNS and Twitter are arguably informal rather than formal channels for learning (both existing outside of the formal institution and are opted-into by individuals) (Vaessen, van den Beemt & de Laat, 2014), the dichotomy of formal and informal is blurred in the context of academic SNS, where formal academic roles and structures are reproduced. Hierarchy has been demonstrated in other contexts to impede learning in networks (Vaessen, van der Beemt & de Laat, 2014); this would suggest that Twitter may be a richer site for academics' professional networked learning than more formalised academic SNS. Preserving academic hierarchy may also reflect differences in social capital more broadly facilitated by the different sites. Network structure has been explicitly linked to social capital; greater bonding social capital being related to denser, more cohesive network structures, and bridging social capital being related to positions linking different communities (Crossley et al, 2015). Both bring attendant benefits and constraints; for example, those with high bonding capital may experience the benefits of solidarity but be constrained by social norms, while those with high bridging social capital may lack support but gain benefits from performing brokerage roles (Burt, 2005). Online social networks have been identified as potentially changing the dynamics of social capital, by offering a mechanism to reinforce weak ties and making latent ties (those which could exist but do not at present) visible (Haythornthwaite, 2002). However, in practice, online networks may also simply serve as an additional channel to reinforce strong ties (Haythornthwaite, 2005); the network structures may suggest that reinforcing strong ties is more likely the role being played by academic SNS. Conversely, the characteristics of network structures observed on Twitter would suggest that this platform may offer more potential gains and opportunities for academics. The more diffuse network structure may allow better circulation of information and less formalised connections may make it easier to establish connections with others who are not already known to academics 'offline'. The differences in Twitter network size and structure according to job position indicate that it is easier for less established academics to gain a sizeable network and following on Twitter in contrast to academic SNS.

It is also worth emphasising that these are but two types of social media platform, and whilst they represent some of the main SNS used professionally by academics (Van Noorden, 2014), use of the sites is only part of the academics' professional networking activities, online and offline. While the analysis has revealed interesting trends in network structure, it can only give limited indications of the dynamic social processes which led to their creation, and the relationship between the networks and academic practiceTo this end, interviews are currently underway to gain the participants interpretations of the network structures. A better understanding of this will help academics understand the roles that different platforms can play and make informed decisions about how to focus their online activities.

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