‘Seeing’ the learning community: An exploration of the development of a resource for monitoring online student networking

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Abstract

The trend to adopt more online technologies continues unabated in the higher education sector. This paper elaborates the means by which such technologies can be employed for pedagogical purposes beyond simply providing virtual spaces for bringing learners together. It shows how data about student ‘movement’ within and across a learning community can be captured and analysed for the purposes of making strategic interventions in the learning of ‘at risk’ students in particular, through the application of social network analysis to the engagement data. The study that is set out in the paper indicates that online technologies bring with them an unprecedented opportunity for educators to visualise changes in student behaviour and their learning network composition, including the interventions teachers make in those networks over time. To date, these evaluative opportunities have been beyond the reach of the everyday practitioner—they can now be integrated into every teaching and learning plan.

Introduction

There is a well-known proverb: ‘it’s not what you know, it’s who you know that counts’. It is a proverb commonly associated with leveraging social networks for professional benefit, and is thus not usually thought of as pertinent to educational success. However, that may well be changing. There is increasing recognition within the education literature of the importance of student social or peer networks to learning, and more specifically to learning performance (Cho, Gay, Davidson & Ingraffea, 2007), a sense of community (Dawson, 2008), class cohesion (Reffay & Chanier, 2003), and information and resource exchange (Haythornthwaite, 2006). This burgeoning research shifts the focus of studies from developing an understanding of the whole network community (entire social group) to examinations of the patterns of behaviour and tie connections...
for individual or ego-networks (Saltz, Hiltz & Turoff, 2004). In doing so, it foregrounds the relevance of the proverb by indicating how specific ego-networks may inform the extent to which who you know leads to educational success.

Despite recognition of the importance of social networks in education milieu (Brown & Adler, 2008; Tinto, 1998), there has been little attention paid to the impact of an individual student’s network on their learning. Thus we have little guidance from the literature about whether the ‘who you know’ benefit applies equally to a learning context as to a career advancement context. Are there different patterns of networking that are demonstrated by high-performing students as distinct from low performers? And if so, how can teachers make use to these patterns to monitor network composition and identify potential at-risk students? In order to begin to explore these questions, this paper elaborates a study that examined the types of relationships (networks) students foster in an online education setting and their impact on learning performance. Specifically, the study explored differences in network composition for low- and high-performing students in order to identify patterns of network behaviour that might have influenced learning, and showed how these findings could be applied as a guide to assist educators in the evaluation of implemented online activities. The outcome was the development and adoption of a network visualisation resource that extracts data from the online environment and graphically displays the student network for easy interpretation.

The ‘social’ in education
The term ‘social’ has for some time now been ubiquitous in educational scholarship. Terms such as social learning (Brown & Adler, 2008), social networks (Haythornthwaite, 2002, 2006), social presence (Garrison, 2007; Gunawardena, 1995) and social architecture (Bogenrieder, 2002) have gained increasing prominence within the literature, testifying as they do to the relational nature and purpose of learning. Historically, the increased focus on the social in education can be traced back to the works of Dewey (1938/1963) and Vygotsky (1978), who maintained that the process of learning is facilitated through individual participation in social interactions. Thus, the development of learning activities congruent with social-constructivism commonly emphasise learner-to-learner interactions within a group engaged in constructing a culture of shared understanding and artefacts.

More than a decade ago, Alexander Astin (1993) foregrounded the importance of peer learning interactions by arguing that an individual's peer network is the ‘single most potent source of influence’ (p. 398) on student growth and development. His premise was built on research demonstrating that the frequency of learning-related peer–peer interactions is positively correlated with student academic performance. Almost a decade later, Richard J. Light (2001) noted that a student’s propensity to participate within small study groups was an accurate predictor of academic success. Furthermore, literature discussing the differences in generational learners, such as Marc Prensky (2001) and others (eg, McWilliam, 2008; Oblinger, 2004) have argued that ‘digital natives’, ‘millennials’ or the ‘yuk/wow generation’ are first and foremost social
learners. This generation of learners have a predisposition to call on peers within an established social network when seeking or providing information, assisting with tasks or evaluating and benchmarking their knowledge platforms.

We have learned more about the learning preferences and dispositions of post-millennial young people through gaming research. Research conducted into gaming environments by John Beck and Mitchell Wade (2006) demonstrates how such learners engage with new phenomena to develop new understandings. New users to online multi-user playing environments seldom engage with the written manual in order to learn the gaming rules, aims, language and culture (Beck & Wade). This is discovered experientially and with the assistance of more knowledgeable members of the gaming community, through what Lave and Wenger (1991) have termed situated learning within a community of practice. In short, the ‘social’ is not the context around learning—it is the learning process itself.

Although it is now accepted that a student’s social network is central for facilitating the learning process, there has been limited investigation of how networks are developed, composed, maintained and abandoned. However, we are now better placed than our predecessors to use digital technologies for the purpose of making learner networking visible. We can see, for example, how individual actors within a specific network draw upon the experience and knowledge contained by the network at large. A student linked to a network containing a high level of experience and knowledge may be assumed to be better positioned to leverage these attributes for enhancing their academic success than their more poorly networked peers. If teachers are enabled to ‘see’ those who are network-poor earlier in their candidature, it becomes possible for them to make timely and strategic interventions to address this issue.

While implemented teaching practices can facilitate an increase in the size and make-up of student networks, there are few methods providing instructors with a process for monitoring, visualising and evaluating the evolution of individual student networks. The following describes a way forward from this impasse.

**Social Network Analysis**

Social Network Analysis (SNA) provides a valuable methodology for examining the patterns of interaction that occur within a group of actors (a network). As such, SNA draws on various concepts from graph theory and structural theory to evaluate network properties such as density, centrality, connectivity, betweenness and degrees. These measures provide a framework for interpreting and developing an understanding of the observed patterns of exchanges that occur between social actors. SNA provides a visual representation of individuals and their place in the network (Wasserman & Faust [1994] provide an excellent comprehensive overview of SNA).

The flexibility and value of this methodology is reflected in the quantity and diversity of studies adopting SNA techniques. For example, SNA has been applied to studies investigating obesity (Christakis & Fowler, 2007); terrorism (Krebs, 2002); business
organisations (Burt, 2004; Gulati, 1995); knowledge management (Cohen & Prusak, 2001); employment (Montgomery, 1991); fashion (Gladwell, 2002); the Internet (Wellman, 1996; Quan-Hasse, Wellman, Witte & Hampton, 2002) and creativity (Dawson, McWilliam & Poole, 2008). In the teaching and learning context, the usefulness of SNA as a methodology to assess student social networks has also been well demonstrated. For example, Haythornthwaite (1999) used SNA to investigate the frequency and types of interactions between distance learners. The author noted that the implementation of small group work activities promoted the development of stronger ties between individuals and a larger, more complex network. Dawson (2008) identified correlations between SNA centrality measures and student sense of community, noting that degree and centrality were noted to be positive predictors of student sense of community. Additionally, the size and complexity of social networks has also been demonstrated to influence student learning performance (Cho et al., 2007).

Notwithstanding how well all these studies illustrate the capacity of SNA to inform and guide teaching and learning practice, the overall extraction and collation of social network data has to date been problematic (Reffay & Chanier, 2002). The collation of the network data is frequently retrieved from techniques reliant upon the notoriously weak technique of participant recall. Thus, the gathered data often require further manipulation before SNA can be performed. Such an approach is not only time-consuming but it also limits the study in terms of the size of the network investigated. This is true of the use of SNA in educational contexts, based as it has been on student reflections on the type and quantity of interactions undertaken with their class peers. Techniques such as student surveys (Cho et al., 2007; Thomas, 2000) and interviews (Haythornthwaite, 2000) remain common approaches for education researchers seeking an insight into the frequency and complexity of the interactions undertaken in a learning network.

More recently, however, the introduction of online communication resources to supplement face-to-face teaching practices and as a core component of distance learning, has provided social network researchers with easy access to detailed event logs listing all online peer interactions. This means that data for student SNA within online units of study can be gathered via the examination of the various communication artefacts associated with the unit, such as chat logs, discussion forum postings, blog posts and comments. The potential richness of these sites for social network data mining provides an opportunity for SNA researchers to extract valid and reliable data regardless of the potential network scale. Moreover, analysis can be based on actual, observed and recorded student behaviour in lieu of participant reflections on action.

**Online education—untapped data**

In online learning, practitioners guided by socio-constructivist principles have tended to rely on the use of social communication tools such as discussion forums, and more recently blogs and wikis, to generate the peer interactions necessary to promote a sense of community. A unique attribute of these online tools (forums, blogs and wikis) is their capacity to retain a historical archive of communication interactions that have taken
place among a group of social actors. For instance, discussion forums retain a search-
able archived history of all messages posted by individual students and teaching staff. Additionally, the format of the discussion forum provides author identification and an indication of the message direction. Put simply, Student A posts a message and Student B subsequently responds—the direction of interaction is from Student B to Student A. These data are commonly captured and stored within an institutional database where they can be readily extracted and collated for further analysis.

The collation and analysis of online learning management system (LMS) data have been utilised by a number of researchers in recent times to illustrate relationships between student user-behaviour online and learning and teaching. For instance, Campbell and Oblinger (2007) combined prior academic results with student online effort to develop a predictive model of student attrition. Dawson (2006) extracted discussion forum data to demonstrate correlations between message frequency and student sense of community. Morris, Finnegan and Wu (2005) noted a positive relationship between time spent online in class discussion forums and overall academic performance. These studies illustrate the capacity for ‘seeing’ user online interactions and so providing teaching staff with ongoing lead indicators of student learning, behaviour and performance.

While commercial LMS generally provide some student tracking data, the difficulty of access, complexity and presentation of these data can and does impede instructor interpretation. Staff often have a limited understanding and experience with the types of data available, and how these data can be applied for benchmarking and evaluating teaching activities and interpreting the relationship between observed student online behaviour and implemented pedagogical practice. These problems can be overcome through the adoption of these types of student data, recently termed academic analytics (Goldstein & Katz, 2005). In short, teaching and learning practices can be enhanced through the development of more pedagogically-oriented information visualisation tools.

The study
Given that learning, as indicated above, is a social process involving multiple exchanges and interactions across a diversity of actors, then to investigate learning is to investigate the form and character of social networks. Thus the application of SNA has been promoted as an effective approach for not only visualising the complexity and attributes of the student network, but to also dissect the intricacies associated with determining individual student learning requirements. The study described below incorporates SNA within an online learning environment to identify differences between individual networks (ego-networks) of high- and low-performing students. In so doing, the study addresses the following research questions:

- Are there significant differences in the network composition between high- and low-performing students?
- Do high-performing students have larger social networks than their low-performing peers?
• Is instructor presence more prevalent in the networks of high- or low-performing students?
• How can the visualisation of student social networks aid pedagogical practice?

Through exploration of these research questions, the study provides education practitioners with a better understanding of the influence peer ties have on individual student learning behaviour and overall performance. Additionally, the study describes the development of a new analytic resource to extract data from the student online learning environment. This visualisation tool provides educators with an opportunity to monitor the impact of implemented learning and teaching activities and the overall engagement of individual students with their peers.

The description that follows is of a component of a larger international research project designed to identify the range of applications for LMS-derived data to inform learning and teaching practice. The study interrogated the data generated through student interactions with an institutional LMS (Blackboard [BB] Vista—formerly known as WebCT Vista). While student tracking data available through the LMS provide an indication of user-time online and the specific sites of enquiry (eg, content areas, assessment, discussion forum, etc), the objective was to refine the broad analysis and focus directly on student activity within the online discussion area. In so doing, it became possible to incorporate elements of data mining and SNA into the analysis.

The data that were subjected to analysis were drawn from a large Canadian University with approximately 42 000 full-time equivalent students and 5000 teaching and sessional staff. Data were collected from a large prerequisite first level chemistry unit (n = 1026) during the September to December 2007 teaching period. The term unit is defined as a focused course of study of approximately 13 weeks in duration comprising a part of a larger programme leading to a specific degree. The investigated teaching unit was offered exclusively as an internal mode of study. This was defined as study undertaken on-campus and comprised more traditional education delivery methods such as face-to-face lectures, tutorials and workshops. However, the teaching unit under investigation also used extensive online resources and activities delivered via the institutional LMS—BB Vista. Thus, although the investigated unit was defined as an internal mode of study, it can be seen to be more analogous with a blended model of learning. Furthermore, it must also be stressed that student participation in the online environment was not mandated nor assessed. However, participation was actively encouraged by the instructor and well integrated with the more traditional learning and teaching activities.

Extracting network data
While many commercial LMS have student tracking capabilities as generic software features, the depth of extraction and aggregation, reporting and visualisation functionality of these data has been disappointingly basic or non-existent. Generally speaking, the student tracking data can report on the time spent online, number of pages visited and the number of discussion forum posts contributed or read. Unfortunately, the
visualisation of these data is commonly restricted to poorly organised tabular formats, or statistical graphs (Mazza & Dimitrova, 2007). As such, the presentation of these quantitative data is limited to a technical analytic context, and remains incomprehensible, fragmented and/or removed from the instructor-implemented pedagogy. This means, among other things, that most academics view interpretation of the observed student behaviour and subsequent alignment with implemented learning and teaching activities as a complex and alien process, requiring extensive knowledge and experience of both statistics and the online learning environment. What is lacking in current commercial LMS tracking functionality is the ability to report on the frequency, depth and quantity of peer-to-peer interactions manifesting within the online learning environment and the provision of visual resources to aid instructor interpretation and thus be of immediate pedagogical use. This point is emphasised by Mazza and Dimitrova (2007), who argue the value of promoting the use of information visualisation techniques for representing graphically the data collated by commercial LMS, insisting that the graphical representation of these data could aid instructor interpretation and evaluation of pedagogy in action.

In order to apply a method for data extraction and visualisation, a resource was developed first to extract the network data and then visually represent the peer-to-peer interactions occurring within the online discussion forum. The visual representation of these emerging networks was designed to facilitate instructor understanding of student online engagement and the impact of specific learning and teaching activities, and to alleviate concerns expressed by network researchers about the complexity they perceived to be associated with the extraction and collation of network data (Reffay & Chanier, 2002). The resource essentially automated the process of extraction, collation, evaluation and visualisation of student network data available as discussion forum postings and interactions.

The information and communication technology (ICT) resource was developed in javascript using Greasemonkey (http://www.greasespot.net/), a Mozilla Firefox browser extension (http://www.mozilla.com/en-US/firefox/). Given proprietary concerns around accessing the database of a commercial system, an external script was deemed a sound alternative. Figure 1 illustrates an example BB Vista discussion forum and the enabled Greasemonkey script. This script is located below the discussion forum page, and when activated, extracts and tabulates the student interactions. These extracted forum data are then exported into Netdraw (Borgatti, 2002), a third party social network visualisation tool. Figures 2 and 3 demonstrate the network visualisation results (sociograms) generated from separate BB Vista discussion forums.

The individual nodes within the sociograms represent all actors, students and staff participating on the online discussion forum. While student names have been removed for the purpose of this paper, the sociograms include student identifiers to make visible the level of network complexity, degree of engagement (individual and class), central nodes in discussion and students potentially isolated from the learning network.
Performing SNA

SNA provided a method for investigating the patterns of interactions and degree of connectedness amongst a set of defined actors. In the study, SNA was applied to the extracted communication logs (discussion forum activity) to determine the network complexity, key central actors and the level of relationships developed. SNA provided an opportunity to reconstruct and visualise the developing student social structure (Harrer, Zeini & Pinkwart, 2005) in order to identify differences in the networks of high- and low-performing students. Learning performance was determined by the academic grade (as a percentage) that students received on completion of the established

Figure 1: Modified screen grab of BlackBoard Vista discussion forum and location of the enabled Greasemonkey script—‘Perform Social Network Analysis’ (student identifiers have been removed)

Figure 2: Sociogram illustrating simple student online network. The nodes represent individual students and teaching staff (names removed). The thicker lines indicate increased levels of communication exchanges between different actors (students and staff) in the network

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teaching unit assessment tasks. Thus, the category ‘high performers’ included all students ranked in the 90th percentile. Low-performing students were derived from the 10th percentile.

The unit discussion forum logs were extracted as ‘vna’ files for exporting into Netdraw (Borgatti, 2002). This social network software then generated a sociogram from the available data. The software also provided options for various centrality calculations, eg, degrees, closeness, betweenness and centrality. A further feature of Netdraw is the ability to refine the network data to focus on individual ego-networks (Figure 4).

Ego-networks are comprised of the interactions and connections from an individual focal point in lieu of the network as a whole. This study examined the ego-networks of the top 10% and bottom 10% (based on ranking of academic grade; n = 207) of all students enrolled in the teaching unit. Each ego-network was interrogated for the number and type (staff, student) of connections. The presence of teaching staff was recorded for each ego-network, providing an indication of teacher accessibility and activity in both high- and low-performing subgroups. Additionally, the mean grade of all actors in a specific ego-network was calculated. This score was repeated for each individual student (high and low performers) to provide a measure of the network composition in terms of learning performance for each subgroup investigated.

**Statistical analysis**

The data derived from the study were analysed using the software package SPSS for Windows (Vers 15.0) incorporating descriptive statistics and nonparametric tests of

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*Figure 3: Sociogram demonstrating a higher level of network complexity. The sociogram also identifies students disconnected from the dominant network.*
significant difference. The nonparametric statistical analysis employed in this study was the Mann–Whitney \( U \)-test. This statistic was used to assess the level of significant difference between the network size and the academic scores of established social ties between high- and low-performing students (90th and 10th percentiles respectively).

Results

Participants and discussion forums

The final student academic grade was used to determine the 10th and 90th percentile groups for the social network investigations. Academic scores ranged from 0 to 98.11%. The participating teaching unit consisted of four discussion forums. Three related to content discussion and specific learning activities and one forum was devoted to general (off-topic) conversation. The student ego-networks for the high and low performers were calculated from the available BB Vista discussion forums \((n = 4)\). This consisted of 2804 messages related to the unit content and learning activities with a further 319 messages posted on the off-topic discussion forum. Because contributions to the unit discussion forums were not mandatory, a small number of students from both the 10th and 90th percentile groups did not participate. The final participant size was 164 representing 79% of the 10th and 90th percentile sampled groups and 16% of the total student class population. Given that the study was specifically seeking to identify differences in online networks of low- and high-performing students, the final sample size was acceptable as representative of the two populations investigated.

Network size

A Mann–Whitney \( U \)-test revealed a significant difference exists between the observed the network size (degree) of low- and high-performing students (Table 1). The results indicate that high performers develop larger social networks than their low-performing
peers. The mean number of actors located in a high-performing ego-network was 5.19 (SD = 9.64, n = 103) in contrast with 1.77 (SD = 3.22, n = 61) for low performers.

**Grades**

Analysis of the mean grade for the ego-networks examined suggested that high-performing students primarily develop connections with students of a similar academic capacity. The mean grade score for high performers networks was calculated to be 77.32% (SD = 14.04, n = 376) (Table 2). Similarly, low-performing students were also more inclined to foster online relationships with peers of a comparable academic score (mean = 59.79, SD = 21.3, n = 80). The specific actor for each ego-network examined was removed from the calculations of mean grade to guard against bias in the results. For example, the inclusion of mean grade calculations with students from the 90th percentile would elevate the observed mean grade. Thus the mean grade represents the network participants only.

**Teacher presence**

The study aimed to determine the degree of teacher prevalence in each of the two student populations examined. Examination of the actors associated with the ego-networks indicated that the teaching staff members were positioned in 81.7% of the high-performing and 34.61% of the low-performing student networks.

**Limitations of the study**

The study of student social networks is a complex undertaking influenced by many external factors. As such, the research design and analysis have potential limitations that impact on the interpretation of findings and broader generalisability. For instance, the

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**Table 1: Mann–Whitney U-test for differences in mean size of ego-networks for high- and low-performing students**

<table>
<thead>
<tr>
<th></th>
<th>Mean degree</th>
<th>SD</th>
<th>Mean rank</th>
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<tbody>
<tr>
<td>High (90th percentile)</td>
<td>5.19</td>
<td>9.64</td>
<td>90.32</td>
</tr>
<tr>
<td>Low (10th percentile)</td>
<td>1.77</td>
<td>3.22</td>
<td>69.30</td>
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<tr>
<td>Z</td>
<td>-2.924</td>
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<tr>
<td>p</td>
<td>&lt; 0.003</td>
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**Table 2: Mann–Whitney U-test for differences in mean grade of actors linked to the ego-networks of high- and low-performing students**

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<thead>
<tr>
<th></th>
<th>Mean grade</th>
<th>SD</th>
<th>Mean rank</th>
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<tr>
<td>High (90th percentile)</td>
<td>77.32</td>
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<td>Low (10th percentile)</td>
<td>59.79</td>
<td>21.3</td>
<td>135.74</td>
</tr>
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<td>-6.934</td>
<td></td>
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<td>p</td>
<td>&lt; 0.001</td>
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development and analysis of student social networks is derived from a single source, namely the discussion forum data. Although the discussion forum is the most widely adopted online communication resource among staff and students at the institution, reliance on this as a sole source of data does exclude any potential social ties that may have developed through face-to-face meetings with peers and staff. Nevertheless, as Haythornthwaite and Wellman (1998) noted, the online environment is a powerful technology for assisting actors in maintaining previously established offline ties and connections. Thus, it can be assumed that, while the online network may not capture the complete student network, it does provide a relatively accurate snapshot of the form and character of the interactions and connections students have developed during their course of study.

Discussion
The study outlined above aimed to explore differences in network composition for low- and high-performing students in order to identify potential patterns of network behaviour that may influence student learning. The findings from the study demonstrate that significant differences exist between high- and low-performing students in terms of their network size and composition. Furthermore, the results suggest—perhaps unsurprisingly—that specific instructor interventions are primarily positioned within the networks of high-performing students. It need hardly be pointed out that this is the obverse of what might be expected if indeed pedagogical attention was to be focused on the ‘most needy’ and the ‘most at risk’. If, indeed, ‘it’s not what you know it’s who know that counts’, then perhaps much could be done for at-risk students through interventions that ensure that they actually ‘know’ their teacher in the first instance.

Whether or not academic teachers may be mobilised to redirect their own networking efforts if they have data to show those who are ‘network-poor’, there is certainly evidence from the study to suggest that the ‘who you know’ proposition is pertinent to educational contexts. While causality cannot be determined in terms of academic performance and network relationships, the clear differentiation in social ties fostered between the two student subgroups supports the view that ‘similarity breeds connections’ (McPherson, Smith-Lovin & Cook, 2001, p. 415). Put another way, the capacity of high performers to attract other high performers into a collaborative learning network structure provides these individuals with direct access to a greater level of social capital than their low-performing peers.

Not all students are responsive to networking possibilities. As Cho et al (2007) found, there are often profound differences in students’ communication style and impact on network composition. They noted that students with a ‘low willingness to communicate’ adopted different network strategies from their more willingly conversant peers. These more introverted students tended to rely on smaller trusted networks while more extroverted individuals formed multiple network ties. The willingness to communicate within a learning group could be related to student confidence and perceived level of understanding of the academic content. Findings of the study indicate that low-performing students develop small networks that are comprised of actors of a similar...
academic capacity. It follows that students with low levels of academic confidence (ie, possessing a novice understanding of the course content) are likely to be less willing to converse with a diversity of peers, and this in turn would result in a smaller network size. As students develop a greater understanding of course content, their willingness to communicate and capacity to answer discussion forum questions may rise.

However, the problem for low-performing students is exacerbated because their ability to develop a greater understanding of the course content is also impeded by the particular character of the network associations they develop. The level of access to the number of advising networks—actors that actively share resources, information and provide guidance—has been demonstrated to positively influence student academic performance (Yang & Tang, 2003). While low-performing students have access to all posted messages, the capacity to draw upon established networks of higher-performing students within the forum is lacking. Essentially, students located within a network of low performers have access to low-level advisors. In contrast, students situated within a network of high performers have access to more knowledgeable advisors. Thus high-performing students have an opportunity to leverage academically stronger ties to facilitate their learning, evaluate their individual understandings and assist with course assessment. Indeed, it would appear that who you know in the network is crucial not just in terms of how students come to know but the nature and quality of the knowledge they actually produce.

All the above implies that academic teachers should be seeking to ensure that their students’ network density (number of possible social ties) is maximised. In a learning context, all students can benefit from access to multiple advising networks through active engagement in a collaborative social learning environment. However, the strong homophilic nature of the learning network suggests that students are self-selecting and regulating those individuals they intend to develop social connections with.

The central premise of a learning community is that members will share resources, information and collaborate in order to assist one another in a common endeavour, presumed to be learning the content of a specific discipline or, as Brown and Adler (2008) noted, ‘learning to be a full participant in the field’ (p. 19). Despite the rhetoric and best intentions of educators to develop a sense of belonging and shared purpose among a group of learners, conflicting demands and priorities placed on students may result in more self-centred reasoning processes. For instance, the normalisation of student grades resulting in academic competition may well militate against sharing, collaboration and advising. It is understandable that, while an institution clings to more performance-oriented goals, its students will focus more on their individual performance than the shared project of community-wide learning. In this context, students develop network ties that are tightly connected to providing direct benefit to the individual.

Not all social ties, of course, are of the same character. Granovetter (1982) maintained that social ties can be classified as either strong or weak. Individuals with strong ties are mutually dependent and share multiple resources. For example, strong social ties are
commonly associated with close personal relationships. In contrast, weak ties represent linkages across more distant and disparate cliques. Thus, weak ties are commonly less emotionally bound than strong ties and more focused on simply exchanging information, ideas and resources. The network patterns observed in the study indicate students are fostering multiple weak ties with selected peers. In this instance, individuals may be less motivated by the possibility of making strong emotional connections and more centred on leveraging networks for personal gain. Richard Florida (2002), author of ‘The rise of the creative class’, suggests that individuals no longer require or seek to build ‘strong’ social ties as these commonly represent more long-term commitments and therefore, constrained mobility. Many post-millennial individuals are now seeking more fluid and diverse social ties. Thus, students can connect and disconnect with the network and still leverage benefit. A long-term commitment to the class network is not required. This is an ephemeral gathering of individuals attempting to rapidly establish ‘flockmates’ (McWilliam & Dawson, 2008) for the greatest personal benefit. In other words, high-performing students have the opportunity of tapping the network when they require with greater ease and fluidity than in the nondigital past. Thus high-performing students have the option of regulating and self-determining the social ties they require for assisting with their academic endeavours. Individual high performers with more altruistic motives may attempt to engage ties with a diversity of students irrespective of perceived academic capacity and therefore direct academic value. However, these results suggest that given student pressures, time constraints and the competitive nature of higher education, these individuals are a minority.

**Instructor intervention**

This study examined the degree of teacher presence within the networks of high- and low-performing students. Interestingly, the teaching staff members were more than twice as likely to participate in the network of a high-performing student as they were in a low-performer network. This is a stark reminder that many students requiring greater academic assistance may actually be receiving less direct teacher intervention. Teaching staff, through their participation and facilitation in the forums, had intended to promote a sense of community in the student cohort. Where a more factual orientation was asked of the students, staff often diminished their own presence to allow time for peer response and assistance, presuming that allowing space and time for peer-to-peer engagements to evolve would benefit the entire student learning community. While staff attempted to respond to all discussion postings, high-performing students posted more conceptual questions and were thus perceived by staff to require some direction and assistance, given that the answers to these types of questions could not be directly located in the prescribed text. Thus, the teaching staff actively intervened to provide direction to new resources or to redirect discussion towards a solution, but the benefits flowed most often to the high performers.

While community-centric teaching practices clearly have direct learning benefits, there are pitfalls that are highlighted in this study. In large class situations, as a result of workload implications, the monitoring of discussion forum interactions is often confined to observations of postings and replies. Over time, unanswered messages are easy
to identify, allowing teaching staff the possibility of rapid and direct intervention. However, the promotion of community is also linked to the number and diversity of learner–learner interactions. The study suggests that the development of a largely homophilic network may well be counter-productive, despite the presence of a community-centric philosophy. The capacity to visualise both class and individual networks provides educators with a resource to better identify potentially at-risk students and to also monitor the allocation and direction of teacher support.

**Conclusion**

The trend to adopt increasing levels of online technologies continues unabated in the higher education sector. As these technologies allow capture and recording of student and staff interactions, they bring with them an unprecedented opportunity for educators to analyse new data sets for informing and improving pedagogical practice. The organic nature of the ICT data provides ongoing analysis and the capacity to visualise changes in student behaviour, network composition and teacher interventions over time. To date, these evaluative opportunities have been beyond the reach of the everyday practitioner—now they can be integrated into every teaching and learning plan.

The findings from the study clearly support the proposition that ‘like-flocks-to-like’ in the ego-networks of high- and low-performing students. High-performing students were more inclined to form social ties with other high academic performers. Similarly, low-performing students developed social ties with other low performers. An added finding was the identification and analysis of the degree of teacher presence within the student networks. It was observed that teaching staff members were more commonly located in the networks of high-performing students. Notwithstanding the commitments they might have to assisting students requiring additional learning support, staff members were largely unaware of the limited level and diversity of forum interactions they had participated in. This pedagogical gap can be filled by means of the ICT-based resource elaborated in this paper, one that can provide a graphical and timely representation of the network, thereby assisting staff to align their pedagogical practices more fully with the learning needs of all their students.

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