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Birds of a feather: The geographic interconnection of Australian universities on Twitter

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Introduction

Online social media systems are increasingly important channels for communication over the Internet (Scellato *et al.*, 2010; Rauniar *et al.*, 2014), providing new ways for individuals and organisations to receive and exchange information (Davis *et al.*, 2011; Li *et al.*, 2012). The growing ubiquity of social media systems, and particularly their use by key higher education audiences means that universities have no real option but to engage with communication via social media (Johnson *et al.*, 2014; Voss and Kumar, 2013). Beyond specific learning and teaching applications, a range of uses of social media by universities is noted in the literature (Wang *et al.*, 2014), including marketing, student recruitment, connecting with alumni, student support services, library services, student mentoring and general communication with the wider community (Palmer, 2013). Social media systems create both ephemeral and enduring connections between users, based on both sharing of transient content (Meeder *et al.*, 2011; Java *et al.*, 2007; Yardi and Boyd, 2010) and formal 'friend/follower' relationships configured within the system environment (Kwak *et al.*, 2010; Leetaru *et al.*, 2013). These network data inherently created by social media tools represent the connections between participants as they interact and, via network analysis, they can be made visible to reveal the previously elusive social processes at play, and to identify strategically important components and participants in the social network (Smith *et al.*, 2009).

In the UK (Hoare, 1991) and many other Western countries, there is a relatively high level of student mobility in on-campus university attendance. However, the university attendance habits of Australian students are somewhat different in this regard, with students being less likely to move between major cities, and university campuses attracting a significant proportion of their enrolment from students who completed the schooling nearby (Edwards, 2009). There is a view in the literature that information technology in general has removed all previous barriers of time and place from higher education (Siemens and Matheos, 2012), and that social media systems in particular are the obvious mechanism by which higher education can expand its geographical reach in the face of financial scarcity (Manlow, 2010). However more recent and extensive canvassing of perspectives on the future impact of technology on higher education finds mixed views (Anderson *et al.*, 2012). More critical reviews of the available research identify that the capacity of information technology to revolutionise education is not evenly distributed across societal divisions of socio-economic status and social class, gender, geography and other factors (Selwyn, 2009). A recent review of the application of social media systems by higher education institutions internationally found that use varied between geographic regions of the world (Kuzma and Wright, 2013). The question of the relationship between social media communities and 'real-life' communities is an area of on-going investigation. (Quercia *et al.*, 2012).

Social relationships and geography are closely related (Backstrom *et al.*, 2010). While views on the relative importance of proximity and social networks vary (Logan, 2012), it has been argued that, 'Perhaps the most basic source of homophily is space: We are more likely to have contact with those who are closer to us in geographic location than those who are distant.' (McPherson *et al.*, 2001: 429) For organisations, research indicates that the social networks are important conduits for knowledge and resource sharing, and that geographical proximity is a significant driver of, and influence on, network formation – possibly because, regardless of organisational size, the key agents of the organisation reside in particular locations (Broekel and Boschma, 2012; Marquis and Battilana, 2009). While the advent of new communications technologies may have reduced many of the constraints of geography on communication, they have not eliminated the importance of locality on interpersonal networking (McPherson et al., 2001). Research has shown that, for personal social networks, the frequency of face-to-face and electronic contacts are positively correlated and complementary, and that the frequency of both types of communication declines with physical distance (Tillema *et al.*, 2010).

The emergence and rapidly growing popularity of online social media systems that allow users to interact without the constraints of their physical location begs the question, 'does offline geography still matter in online social networks?' (Kulshrestha *et al.*, 2012: 202) Based on data from 85 million geo-tagged photos posted on the photo sharing site Flickr, it was found that a small number of spatial and temporal co-occurrences was a strong predictor that the owners of the photographs had a social tie (Crandall *et al.*, 2010). One large scale investigation of four online social networks with geographic information (BrightKite, FourSquare, LiveJournal and Twitter) found that many users had short-distance links, and that clusters of friends were often geographically close (Scellato et al., 2010). An investigation of nearly 500,000 US users of the LiveJournal blogging site found that about 70 per cent of the influence on whether two users were friends was controlled by geography, and that the probability of friendship was inversely proportional to the distance separating the users (Liben-Nowell *et al.*, 2005). Based on the data from 2.9 Million US Facebook users that listed an address, an algorithm that assumed a user was in close proximity to their friends was able to infer the physical location of nearly 70 per cent of users to within 25 miles, and taking into account how often users interacted improved performance, suggesting that physically closer users interacted more often (Backstrom et al., 2010).

Twitter (twitter.com) is a large and growing social network system that is based on 'microblogging' – users can post short messages limited to 140 characters, known as tweets, to other users that follow them, and can read a timeline of tweets from the users that they themselves follow (Kwak et al., 2010). Twitter data contain incomplete geographic information about users, although methods exist for inferring and improving user location (Davis et al., 2011). Documented case studies exist on the use of Twitter data for the spatiotemporal modelling/monitoring of large-scale real-time events, such as H1N1 influenza disease activity in the US (Signorini *et al.*, 2011); earthquakes in Japan (Sakaki *et al.*, 2010), and, correlations between state-based tweet content and known state-based behavioural risk factors, and tracking of reporting of seasonal allergies by state in the US (Paul and Dredze, 2011).

Research has established that, rather than becoming irrelevant, geography continues to exert a significant influence on the way users interact in the Twitter environment (Kulshrestha et al., 2012; Takhteyev *et al.*, 2012). The physical locations of other users following and/or followed by a particular Twitter user have been shown to be important predictors of the physical location of that user (Davis et al., 2011; Li et al., 2012). The degree of connection between users tweeting on location-specific topics on Twitter was found to be significantly higher than for those tweeting about general topics, indicating that physically local Twitter networks are more densely connected (Yardi and Boyd, 2010). For individual Twitter users, based on their follower/following connections, it was found that the majority of users have geographically local networks, and using four measures of ‘social strength’, the stronger the ties, the more geographically local the network (Quercia et al., 2012). At the level of countries, based on nearly 52 million Twitter users, when the follower/following connections between countries were normalised and ranked, strong groupings based on geographic region and/or common language were observed, suggesting that the offline physical world influences the online Twitter social media world (Kulshrestha et al., 2012).

A review of the research on social media in higher education reported on various documented uses of social media by higher education institutions and students, the levels of use by institutions and students, and identified affordances and limitations of social media, but was silent on research relating to the nature of inter-institutional connections via social media (Davis *et al.*, 2012). Likewise, the wider literature review conducted for this research on the use of social media (including Twitter) by higher education institutions found that existing literature largely focusses on investigations into the levels of use, the purposes of use, and the content of social media communications. Use of social media by organisational stakeholders is voluntary (Zhao *et al.*, 2011), so it is important for an organisation to attract a critical mass of members (followers) – ‘Followers are Twitter’s most basic currency.’ (Hutto *et al.*, 2013: 821) Rather than focussing on the quantity or content of the messages passed between Twitter users, this paper presents research investigating the connections created by the follower/following relationships between Australian university Twitter accounts. In particular, it seeks to answer the question, ‘Does physical geography influence the connections between Australian universities on the Twitter social media platform?’ It is important to note that the work presented here is not an investigation into the educational and academic uses of Twitter for teaching and learning, but rather considers only the more generic, organisation-level communication and marketing uses of Twitter by Australian universities.

Method

During mid-May of 2014, the Internet home pages of all 39 recognised Australian universities (Universities Australia, 2014) were inspected to identify an advertised official Twitter account. Where a university advertised more than one Twitter account, the principal account was isolated. A ruling was obtained from the relevant institutional human research ethics committee that the use of publically accessible historical Twitter data did not require formal ethics approval for research purposes. Each identified Twitter account was assigned a random identifier based on the ‘home state’ of their principal/main campus to provide anonymity. For those states where there is only a single university, and for the one case of a multi-state university, a shared ‘home state’ identifier (‘o’ = Other) was used to provide anonymity. For all identified Australian university Twitter accounts, the data relating to all other Twitter accounts following each university, and all other Twitter accounts followed by each university were harvested using the Google spreadsheet utility provided by Martin Hawksey (Hawksey, 2011). The data thus collected also contained information about the inception date of all university Twitter accounts.

All individual dataset pairs were visualised as scatterplots to visually assess if there were any suggestive relationship between them. For any relationships thus observed, the appropriate form of regression analysis was employed to assess the significance and explanatory power of any model produced. One method for representing Twitter follower/following relationships is a directed network (Meeder et al., 2011). Figure 1 shows the network visualisation schema used in this paper. Twitter accounts are represented as ‘nodes’, and a follower relationship is represented as an ‘edge’, with the direction of the edge indicating the direction of the follower relationship. For example, in Figure 1, Uni 1 and Uni 2 follow each other reciprocally, as do Node C and Uni 2. Uni 1 follows Node A, and Node B follows both Uni 1 and Uni 2. In the network diagrams used in this paper, edges are presented as curved lines, and the direction of the follower relationship is clockwise around the edge.

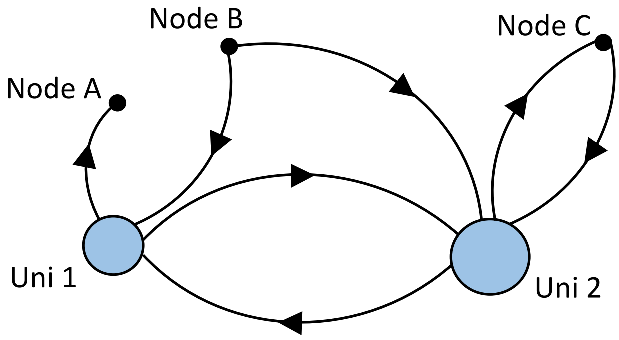

Figure 1.
Twitter relationship network visualisation schema used in this paper

The follower/following data collected were exported from the Google spreadsheets into Microsoft Excel (Microsoft, 2013) spreadsheets. All of the data were consolidated into a single spreadsheet, exported in a comma separated values (CSV) format file, and then imported into the Gephi program (The Gephi Consortium, 2012) to visualise the follower/following network embodied in the data. While there is a single topological arrangement of the data for a given network, it can be visualised in many ways. The Gephi program provides a range of algorithms that can be used to lay out a network according to a set of rules for positioning all of the nodes. In the work presented here the Yifan Hu (Hu, 2005) network layout algorithm was used. The Yifan Hu algorithm is a type of ‘force directed’ algorithm. Generically, force directed algorithms assign ‘attractive’ forces between the endpoints of each edge, and ‘repulsive’ forces between all nodes in the network. The structure of the network is then iteratively simulated using a set of configuration parameters until it reaches an equilibrium state (if possible) where the net attractive and repulsive forces on all nodes are in balance. The Yifan Hu layout algorithm has the advantages that it is both efficient in iterating to a final layout and produces high quality results for large networks. Force directed network layouts position more closely together those nodes that are most strongly connected.

To aid in the interpretation of the network thus produced that contained a large number of nodes (Twitter accounts) and edges (follower relationships), the following formatting was applied to the Gephi layout:

- All nodes were sized in proportion to the total number of edges connecting to them, that is the total count of Twitter accounts that they follow plus the total count of Twitter accounts following them;
- each home state grouping of university account nodes, including the single nodes for states with a single university and the multi-state university, was assigned a separate, bright non-white colour;
- all non-university nodes, were assigned the colour white; and
- each edge was assigned the colour obtained by mixing the colour of the nodes at both ends of that edge.

The outcome of these formatting actions meant that:

- nodes representing university Twitter accounts were relatively large and bright;
- all other nodes were very small – effectively invisible in comparison to the university nodes; and
- edges connecting to a brightly coloured university node had a similar but somewhat less bright colour.

Results and discussion

One of the 39 Australian universities did not advertise a Twitter account, and a subsequent search did not locate one. Table I shows a range of basic statistics for the Twitter accounts of the 38 Australian universities identified.

Table I.
Basic Twitter account statistics for Australian universities

University	Followers	Following	Months active	University	Followers	Following	Months active
a1	7274	2097	62	q6	8853	968	58
a2	6973	680	60	q7	9438	764	66
n1	2125	2231	55	q8	4829	98	67
n2	5787	3305	67	q9	6472	104	49
n3	4676	2476	58	s1	15990	2136	62
n4	642	241	6	s2	13169	1635	62
n5	5710	873	63	s3	11215	1302	69
n6	4869	332	58	v1	10178	1878	68
n7	15686	943	72	v2	6301	712	48
n8	11546	277	61	v3	11538	570	67
n9	25864	224	63	v4	3293	144	60
o1	1967	312	61	v5	26786	933	69
o2	3594	764	62	v6	33087	836	72
o3	3877	651	55	v7	21430	514	83
q1	994	1254	24	v8	19039	305	44
q2	1300	416	28	w1	2974	1729	63
q3	5097	1028	47	w2	4927	2239	62
q4	1572	220	51	w3	6841	2877	60
q5	1256	172	41	w4	13764	1907	60

a = Australian Capital Territory n = New South Wales o = Other q = Queensland
s = South Australia v = Victoria w = Western Australia

The relationships between the account statistics were visualised as scatterplots, and one suggestive relationship was observed, as presented in Figure 2.

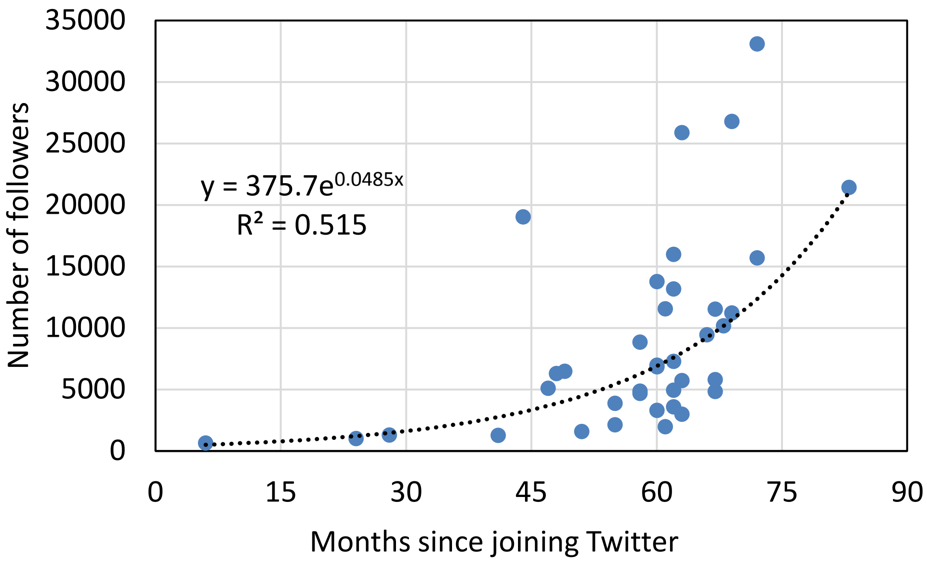

Figure 2.
Scatterplot of time since joining Twitter versus number of followers

The number of followers a user has is an important measure of influence and connection on Twitter (Kwak et al., 2010; Yardi and Boyd, 2010). While Figure 2 is composed of discrete data points from different universities, it suggests that there is a relationship between the time duration since a university has joined Twitter and the number of followers that its account has. Non-linear regression analysis finds that an exponential model, relating number of followers to time since joining Twitter, with the parameters shown in Figure 2, is significant ($p < 4x10^{-7}$) and explains just over half (51.5 per cent) of the variation in the observed data. The dotted line shown in Figure 2 shows the ideal relationship predicted by the model. Interpretation of the exponential model parameters indicates a doubling of follower numbers every 14.3 months. While exponential growth cannot continue indefinitely, periods of exponential growth in Twitter follower numbers have been observed previously (Hou *et al.*, 2013). Figure 2 shows a small number of 'outlier' universities that appear to actively recruiting more followers than most other universities, and at a faster rate than otherwise typically suggested by the time-based exponential growth model.

Figure 3 presents the network visualisation of the collected follower/following data for Australian universities as produced by the Gephi program, based on the schema presented in Figure 1 and using the formatting described in the Methodology. Figure 3 also provides a colour legend for those university Twitter account nodes for the states of Australia containing more than one university. The letter labelling of the legend is that given in Table I.

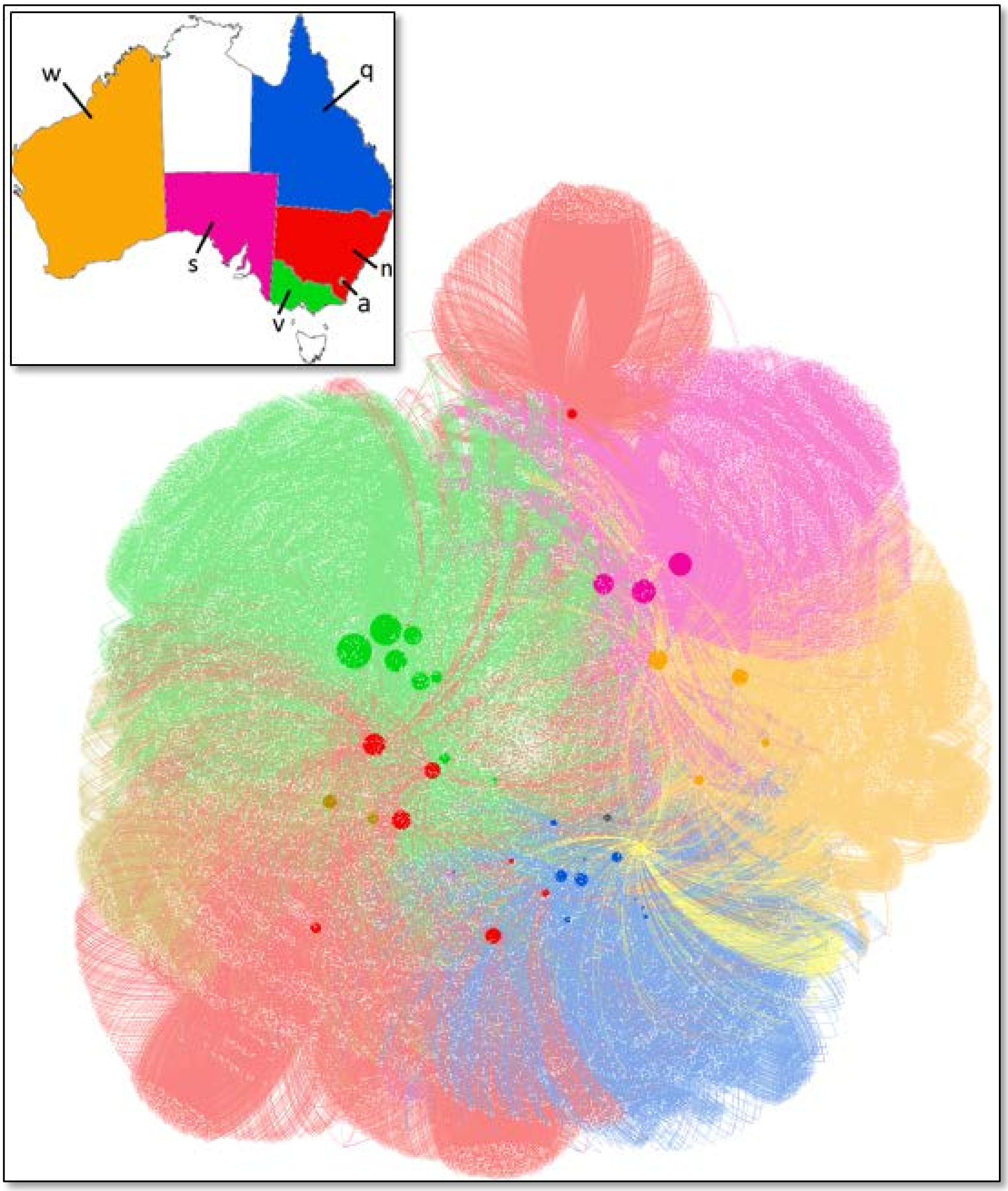

Figure 3.
Twitter follower/following network for Australian universities

While Figure 3 is not straightforward to interpret, one feature that can be seen, particularly at the mid-top and lower-left, is edge loops representing reciprocal following relationships of the kind between Uni 2 and Node C in Figure 1. As noted above, the relative colour and size of the non-university nodes renders them invisible at the far ends of the follower/following edge loops. The other notable feature in Figure 3 is the presence of coherently coloured, cloud-like regions comprised of large numbers of edges connected to university nodes with the same colour. A key aim of this paper is explore the geographic relationship between Australian university Twitter accounts. Figure 4 clarifies the location in the follower/following network of all of the university nodes by removing all of the edges and all non-university nodes, while retaining the university nodes in their original positions as determined by the Yifan Hu layout algorithm. In Figure 4 all university nodes are labelled with the identifiers given in Table I, and retain their colouring from Figure 3.

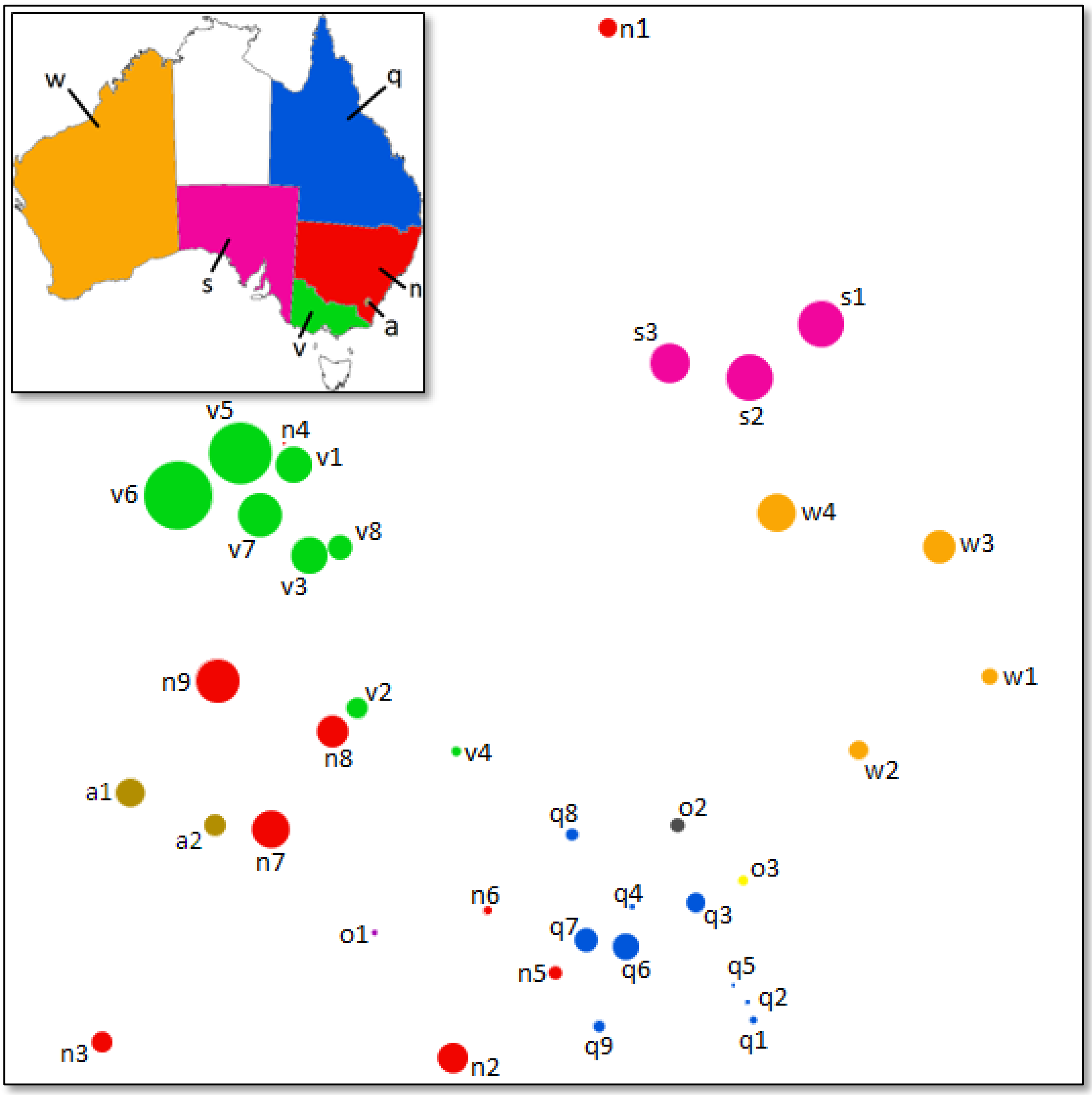

Figure 4.
Alternate version of Figure 3 showing only university nodes

Setting aside the cases of the two single university states, and the multi-state university (o1, o2 and o3 – in no particular order), there is apparent a relatively strong clustering of university nodes on the basis of state. The Yifan Hu layout algorithm combines repulsive forces that push all nodes apart and attractive forces based on the connections between nodes. The consequent clustering of nodes by state suggests that there are strong geography-based intra-state follower/following connections between universities – both directly between universities, possibly reciprocally, and also indirectly via follower/following connections through third-party Twitter accounts, such as those with Node B in Figure 1. In addition to the strong clustering of university Twitter accounts at the intra-state scale, there is evidence of further geographic clustering at the inter-state scale. At the mid-right of Figure 4 is the group of Western Australian (w) universities. Moving clockwise around, both the nodes in Figure 4 and the map of Australia legend, we arrive at Queensland (q). Clockwise again and we arrive New South Wales (n). Associated with New South Wales, both in the Twitter account node layout and physically in Australian geography, we have the Australian Capital Territory (a). Further still clockwise and we reach the generally strongly clustered university Twitter account nodes of Victoria (v). Finally, between Victoria and Western Australia we find the nodes for South Australia (s).

Apart from the three ‘Other’ universities that, inherently, do not have strong intra-state links, there are few significant departures from the intra-state and inter-state geographic relationships between university Twitter accounts observed in Figure 4. University n4 can be seen clustered with the Victorian group of universities rather than with the other universities in New South Wales. The node size of university n4 is relatively small – in Figure 4 node size is proportional to the total number of follower-plus-following connections. Table I shows that university n4 has both the smallest number of followers, and the smallest count of followers and following combined, by a significant margin. Similarly, it has the ‘youngest’ Twitter account by a factor of four. Figure 2 suggests that the number of followers is at least partially dependent on the time since joining Twitter, so it is not surprising that university n4 has a low number of followers. The general principles of operation of the Yifan Hu network layout algorithm depend on the number and nature of connections to determine the position of nodes. It seems that university n4 is yet to become well connected to other nodes associated with the New South Wales group of universities.

The other visually striking ‘outlier’ is university n1, positioned alone at the top of Figure 4, well apart from the other New South Wales university nodes. Davis et al. (2011) demonstrated a method for inferring the geographic location of Twitter users based on the location information supplied by their ‘friends’ (those users that they have reciprocal follower/following relationship with). Further, they found that the location uncertainty of a subject Twitter account increased if it had too few or too many friends. Using the data in Table I, it is possible to compute a ‘friendship index’ for each university from the number of reciprocal following relationships divided by the total follower and following count. If all followers are also followed, the maximum index value of 0.5 will be attained. University n1 has a friendship index of 0.446, nearly twice as high as the next highest university, and much higher than typical. University n1 has nearly the same number of followers as Twitter accounts that it follows, and a high proportion of the accounts in both categories are identical. Given that the followers of a Twitter account can’t be directly controlled, it seems likely that university n1 is simply automatically following back nearly all of its new followers. Such an indiscriminate creation of following links may create a higher than normal proportion of geographically random connections, and may account for the observed isolated position of the node for university n1 in Figure 4.

There are some limitations to note regarding the research presented here. It represents a point-in-time snapshot of the connections between Australian universities on Twitter in mid-May 2014. As Figure 2 suggests, the number of followers a user has is at least partially dependent on the time since joining Twitter, so the follower/following connections of Australian universities may have changed significantly in the interim. Figure 2 itself is comprised of discrete data points from different universities at the same point in time, rather than the time series of the count of followers of any particular university, so it may not accurately reflect the general follower-versus-time relationship. The visualisations presented in Figures 3 and 4 are two dimensional only. It is possible that a three dimensional layout algorithm might produce a network visualisation offering additional insights into the connections between Australian university Twitter accounts. The value of the two dimensional network visualisation here is that it allows direct comparison to the two dimensional physical geography of Australia. It is now common for Australian universities to have multiple campuses, including outside of their 'home' state, although these 'satellite' campuses are typically much smaller than the principal/home campus, and it is likely that the official social media content of the university would emanate from the home campus. It is also now common for Australian universities to house many different Twitter accounts – many academic and administrative units operate their own university-related sub-accounts. This research focused on the primary advertised Twitter account of universities, but it is likely that other networks of relationships exist between subordinate university Twitter accounts. As the follower/following counts given in Table I indicate, the network visualised in Figure 3 is based on many tens of thousands of nodes and edges. While this is a large network, some of the related research mentioned in the Introduction is based on datasets of hundreds of thousands or millions of users, and up to billions of follower/following relationships, so there may be influences of network scale that are different to those observed here. There are limitations with the geographic location information that can be obtained about Twitter users, with many accounts providing limited, made up or no location information (Davis et al., 2011; Leetaru et al., 2013; Yardi and Boyd, 2010), however the analysis presented here did not rely on user account location data provided by the Twitter system. Perhaps most fundamentally, the data set used here is Australian only, so the findings should be extended internationally with caution.

Conclusion

It would be intuitive to assume that online social media systems operate essentially independent of geography, limited only by the reach of the Internet. However much research has found that geography continues to exert a significant influence on the way users interact in the online social media environment. Considering Australian universities, it was found that geography appears to play an important role in determining the relative level of connection between Twitter accounts. Using the Yifan Hu layout algorithm to visualise the follower/following relationships of Australian universities it was found that: i) at the intra-state level, most university Twitter accounts cluster with other universities from the same state; and ii) at the inter-state level the relative position of the state-based clusters follows the national geography of Australia. Two obvious exceptions to these findings had unique follower/following characteristics. An additional finding was that the number of followers that an Australian university Twitter account has at any time after inception is in part explained by a model that is an exponential function of time since inception.

Noting that the analysis presented here was focussed on university organisation-level communication and marketing, rather than educational uses of Twitter communication, there are several implications for practice from these findings. Australian universities are potentially not taking full advantage of the possible reach of online social media systems to communicate to a wider and more physically dispersed group of stakeholders. There is an opportunity to reach beyond the naturally geographically restricted connections observed here, to actively seek and target new audiences, and to realise the often cited benefits of online social media for higher education relating to increased connection across physical and digital frontiers. Most Australian universities offer off-campus, distance and/or online study programs to students based anywhere nationally or internationally. The promotion of such learning opportunities via social media channels will be necessarily sub-optimal if the principal viewers of such communications are from relatively close geographic locations.

Conversely, by capitalising on the strong 'locality' observed in social media connections, it would be possible for a university to become a desirable source of information that is likely to be of interest to, and valued by, local constituents.

Australian universities should understand their social network connections, benchmark their network profile, and continue to monitor both their growing network and their place in it as it evolves over time. Relevant content and effective modes of interaction are of primary importance in social media communication, but without a critical mass of followers, social media messages largely miss their mark. Followers are important on Twitter, and appear to accrete organically over time to some extent. However, time 'explains' only about 50 per cent of the model of follower growth observed here, so there is a role for Australian universities to have active strategies to increase their numbers of followers and, ultimately, their influence on the Twitter social media system. This paper contributes to the research literature on university use of social media by addressing the so far largely silent area of inter-institutional connections via social media, and the influence of physical geography on the connections between (here Australian) universities on the Twitter social media platform. It also offers a practical methodology for those interested in further research in this area.

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