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Visualising the Social Media Conversations of a National Information Technology Professional Association

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ABSTRACT

Social media systems are important for professional associations (PAs), providing new ways for them to interact with their members and stakeholders. Evaluation of the impact of social media is not straightforward. Here text analytics, specifically multidimensional scaling visualisation, is proposed as an approach for the characterisation of the large scale 'conversations' occurring between an information and communication technology PA and its stakeholders via the Twitter social media system. In the case presented, there was found to be a significant level of congruence between the corresponding visualisations of tweets from the PA, and tweets to/about the PA, although differences were also observed. The new method proposed and piloted here offers a way for organisations to conceptualise, identify, capture and visualise the large-scale, ephemeral, text conversations about themselves on Twitter, and to assist them with key strategic uses of social media.

KEYWORDS

Data Visualisation, Information and Communication Technology, Professional Associations, Social Media, Twitter

INTRODUCTION

Online social media systems have created new ways for individuals to communicate, share information and interact with a wide audience (Lee, Reinicke, Sarkar, & Anderson, 2015; Suddaby, Saxton, & Gunz, 2015). For organisations, social media provide new avenues for communication and collaboration with their stakeholders (Alfaro, Bhattacharyya, & Watson-Manheim, 2013). Professionals are also using social media to connect with other individuals who share similar interests (Bacigalupe, 2011). For information and communication technology (ICT) professionals and organisations, there is a natural affinity for the use of online social media systems (Johnson, 2015; Pramod & Bharathi, 2016).

PAs have been using online communication networks for information sharing prior to the emergence of modern social media systems (Wasko & Faraj, 2005). However, the rapid adoption of social media and mobile communications has dramatically expanded connectivity options for PAs, and indeed has changed the role and nature of PAs (Dawson, 2016). Suddaby et al. (2015) note that, in North America, the social media activity of the 'Big 4' accounting firms is contributing to the domain expansion of accounting work at least as much as any activity of the relevant PAs. While

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fundamental professional formation and development continues to be provided by formal learning environments, such as universities, social media have created new forms of flexible and distributed professional learning (Dale, 2016). Social media provide a knowledge diffusion infrastructure to connect the 'push' of information from PAs to the 'pull' demand for information from practitioners and the public (Dearing & Kreuter, 2010). The impact of social media systems on PAs continues to be significant, and while there is substantial literature relating to the general use of social media by organisations (Alfaro et al., 2013; Culnan, McHugh, & Zubillaga, 2010), and the use of social media by professional associations (PAs) is well documented descriptively (Dawson, 2016), the research-based literature on the effective use of social media by PAs is currently much more limited.

The potential benefits of social media for PAs do not accrue automatically. Micieli and Tsui (2015) observed that, for the ophthalmology profession internationally, related patient advocacy groups were more active in social media than professional organisations. PA members may not understand social media, or they may be concerned about confidentiality or privacy issues (Bacigalupe, 2011). PA members may find the ephemeral nature of social media posts, or the fact that interaction/activity levels can be low until a critical mass of users become connected, do not suit their intended purpose(s) for social media engagement (Colley, 2014). Social media continue to evolve - an investigation into the use of social media systems by library and information systems (LIS) professionals found that, over the period 2006-2009, the use of blogs by LIS PAs declined by 50 per cent, and this was attributed to the emergence of newer social media platforms such as Facebook and Twitter (Torres-Salinas, Cabezas-Clavijo, Ruiz-Pérez, & López-Cózar, 2011). There is evidence that the benefits to organisations of involvement in social media are enhanced when they actively engage with it (Alfaro et al., 2013; Culnan et al., 2010; Gallagher, Psaroulis, Ferguson, Neubeck, & Gallagher, 2016), however many authors note the need for additional research on the use of social media systems by PAs (Bacigalupe, 2011; Colley, 2014; Gallagher et al., 2016; Hemsley & Dann, 2014; Suddaby et al., 2015).

A number of existing investigations addressing the use of social media by PAs focus on the Twitter social media platform (Gallagher et al., 2016; Hemsley & Dann, 2014; Micieli & Tsui, 2015). Twitter (twitter.com) is one widely-used social media tool employed by organisations (Culnan et al., 2010). Twitter is a popular 'microblogging' service where users can post quick, short messages (up to 140 characters at the time of this research, but now doubled to 280) called 'tweets', which may contain links to other online material such as photos and websites, to their 'followers' who have subscribed to their Twitter account (Chew & Eysenbach, 2010). A user can 'retweet' to all of their followers a tweet that they receive from another user (Gallagher et al., 2016). Tweets can be directed specifically to other named user accounts, or broadcast generally to all followers of the sending account. Including the 'handle' of another Twitter account in a tweet is a 'mention' of that user. Tweets can contain a 'hashtag' (a keyword prefixed with a '#') such that a search can be performed to locate all tagged tweets (Osborne, 2011). Except for the content of tweets from protected (private) accounts, all tweets are effectively broadcast to 'the world' and are publicly discoverable via a search (Honeycutt & Herring, 2009).

It has been observed that, although it was not specifically designed for it, Twitter has been appropriated for conversational interactions (Honeycutt & Herring, 2009), and that conversations between individuals on Twitter occur frequently (Java, Song, Finin, & Tseng, 2007). A well-established use of Twitter as an online forum for conversations is at conferences, where tweets including a conference-related hashtag collectively create a real-time 'backchannel' for information sharing and discussion (Hansen, Smith, & Shneiderman, 2011). Such conference backchannels allow people remote from the conference to participate in the conversations, and tweets containing the conference hashtag can be collected at a later date for analysis (Sopan, Rey, Butler, & Shneiderman, 2012). A more recent development is the 'tweetchat' – an organised online conversation that is decoupled from any physical event, and which takes place wholly, virtually, synchronously and in a distributed manner on Twitter (Gallagher et al., 2016). PAs (cardiac) have been observed attempting 'join the conversation' on Twitter by posting content containing relevant hashtags, though largely in a one-way/'broadcast' manner (Gallagher et al., 2016). It may not be feasible for a PA to engage extensively in a one-to-one conversation on Twitter, but it is possible to post content that stimulates conversations between other users (Suddaby et al., 2015). Regardless, it is important for organisations to realise that conversations about them will take place on social media, and that they should ideally monitor what third parties, including competitors, are saying to and about them (Alfaro et al., 2013).

Evaluation of the impact of social media activities is not straightforward (Culnan et al., 2010). In many cases, the data are ephemeral (Colley, 2014; Osborne, 2011). A range of complimentary research methods can be used to characterise social media activity. Descriptive statistics (number of tweets/retweets/mentions, etc.) can be compiled to show the magnitude of different aspects of social media activity (Gallagher et al., 2016). The frequency of different types of tweets over time can be visualised to show the time sequence of social media activity (Sopan et al., 2012). The network data inherently created by social media platforms can be used to make visible the connections between participants (Hansen et al., 2011; Palmer, 2017).

A range of approaches to characterising Twitter 'conversations' can be found in the literature. Conversations on Twitter have been identified variously based on hashtags, retweets, and mentions (Honeycutt & Herring, 2009; Murtagh, Pianosi, & Bull, 2014; Pearce, Holmberg, Hellsten, & Nerlich, 2014). Honeycutt and Herring (2009) report on the use of the VisualDTA tool to visualise a connected sequence of tweets, but note that it becomes difficult to track extended conversations between more than small groups of participants. Hansen et al. (2011) describe using the NodeXL tool for viewing the evolution of Twitter networks over time based on tweets matching particular search criteria. This provided insights into who was tweeting on a topic and when, but not about the content of those tweets. Pearce et al. (2014) used statistical techniques to reveal communities in Twitter networks associated with the theme of the 2013 Intergovernmental Panel on Climate Change. They also focused on the connections between Twitter users and not the content of their conversations. A method for conceptualising, identifying, capturing and visualising the large-scale textual conversation on Twitter is not apparent in the literature, and such a method would be valuable for an organisation such as an ICT PA.

The Australian Computer Society (ACS) is the professional association for Australia's ICT sector. More than 22,000 ACS members work in business, education, government and the community. The ACS exists to create the environment and provide the opportunities for members and partners to succeed. The ACS strives for ICT professionals to be recognised as drivers of innovation in our society, relevant across all sectors, and to promote the formulation of effective policies on ICT and related matters (see: www.acs.org.au). The Twitter account handle of the ACS is @ACSnewsfeed. The online nature of social media suggests that they would naturally be an important component of the communication channels used by the ACS, and by ICT PAs generally.

OBJECTIVE

Recent social media research has proposed content analysis as an important element of understanding what is being shared by participants in social media conversations (Badge, Saunders, & Cann, 2012), including for the Twitter social media platform (Pearce et al., 2014), and specifically in relation to the use of Twitter by PAs (Micieli & Tsui, 2015). The work presented here responds to the identified need for more research on the ways that PAs use social media. It uses publicly available data for analysis and visualisation to characterise the engagement of one PA with the Twitter social media platform. It offers a method for conceptualising, identifying, capturing and visualising the large-scale conversation on social media relating to a PA. Specifically, it uses text analytics and visualisation to address the proposal in the research literature that content analysis of tweet text will be a useful approach to characterising online conversations on the Twitter social media platform. The research presented here is an initial investigation that provides useful insights for the ACS, as well as validating a methodology for future work.

METHODS

A ruling was obtained from the relevant institutional human research ethics committee that the collection and use of publicly accessible Twitter data were exempt from formal ethics approval for research purposes. In the work presented here, no Twitter accounts are identified by name, except for those whose owners expressly agreed to be identified. The ACS is the PA that is the subject of the investigation presented.

A public application programming interface (API) provided by the Twitter platform allows data to be directly collected from the system (Chew & Eysenbach, 2010; Suddaby et al., 2015). The functioning of the Twitter system means that the results from a search for mentions of an account are limited in quantity and time period (Hansen et al., 2011). To build a continuous record of tweets from, and mentions of, an account requires the routine capturing and compilation of Twitter search results. By accessing the Twitter API, the NCapture program (QSR International, 2017) is able to capture publicly available Twitter data at that point in time. From the beginning of September 2013 until the end of August 2017, weekly searches for mentions of the @ACSnewsfeed account were performed and captured. The NVivo program (QSR International, 2016) was used to convert the captured Twitter data into Microsoft Excel (Microsoft, 2013) spreadsheets for further processing and analysis. The @ACSnewsfeed Twitter data set was separated into four sets of 12 months in duration (September through August), and each annual set was separated into two subsets: i) tweets from @ ACSnewsfeed; and, ii) mentions of @ACSnewsfeed. The text analytics software package KH Coder (Higuchi, 2016) was used to analyse and visualise the text content of these eight Twitter data subsets to show the major themes present. KH Coder supports a range of text data analysis and visualisation methods – the one used here was the multidimensional scaling (MDS) plot.

Text analytics typically requires pre-processing of the source text to achieve the best analysis result. The Twitter data were exported in plain text format, converted to all lower case, and imported into KH Coder. Common English words and parts of speech, such as 'the', 'and', 'a', etc., add little to the analysis, and their relatively high frequency generally masks other significant terms (Bolden & Moscarola, 2000). KH Coder supports the use of a stop word dictionary, in which common words to be ignored in the analysis may be specified. The default English stop word dictionary supplied with KH Coder was adapted for use here. Information systems (IS) and ICT related words (computer, system, IT, IS, etc.) were removed from the stop word list – acknowledging that removing 'IS' and 'IT' will cause occurrences of the plain text 'is' and 'it' to be included in the analysis here. A second issue that can mask the significance of terms in text analytics is the presence of inflected and/or derived forms of words, for example, a root word such as 'see' may also be present in the source text as 'sees', 'saw', 'seeing', etc. Lemmatisation is a process to consolidate inflected and derived words into their root form, so that the underlying concept is accorded its due weighting based on frequency of occurrence (Bolden & Moscarola, 2000). The default English lemmatisation algorithm implemented by KH Coder was used here.

MDS computes a measure of 'distance' between all pairs of text terms, and then seeks a lower dimensional representation of the terms, such that original distance values between all term pairs are displayed with the least possible error (Namey, Guest, Thairu, & Johnson, 2007). KH Coder supports a number of distance measures and dimensional reduction techniques – the Jaccard distance measure (Netzer, Feldman, Goldenberg, & Fresko, 2012) and the Kruskal method for dimensional reduction (Chen & Buja, 2009) were used here. Words/terms clustered close together in the resultant MDS visualisation are generally found more frequently close together in the source text, and may reveal key themes in the Twitter posts. Two-dimensional visualisations were produced here for ease of interpretation. Based on specifying the minimum frequency of occurrence of a term for inclusion in the MDS analyses and visualisations, terms appear as circles/bubbles in the plots, and the relative frequency of terms is indicated by the size of their bubble. The resultant MDS visualisations contained the names of some people and organisations, as well as Twitter topic hashtags that might potentially identify some participants. Any such identifying terms were de-identified by block replacing them in the source test with unique generic identifiers – e.g., 'person_a', 'organisation_b', etc. KH Coder provides a key-word-in-context (KWIC) concordance feature that can be used to identify locations in the source data that contain one or more specified terms within a specified word distance of each other (Bolden & Moscarola, 2000). The KWIC concordance feature was used to interrogate the Twitter source data to aid in interpreting the MDS visualisations.

Two-dimensional planar projections of text term elements of tweet content have been used previously as an approach to visualise the narrative conversation in Twitter data (Murtagh et al., 2014). Here paired MDS visualisation results from annual sets of tweet text content 'from' and 'to/about' @ ACSnewsfeed are used as a method to conceptualise and 'see' the large-scale 'conversation' between the ACS and its audiences on the Twitter social media platform. The dominant themes articulated by both 'sides' are revealed, and the level of congruence or otherwise between the ACS and corresponding Twitter participants in the annual time period windows can be assessed. The results obtained and a discussion of the observed results are presented.

RESULTS AND DISCUSSION

Data and Visualisations

Twitter 'mention' data rely on the Twitter public search interface, so there is no guarantee that the mention dataset here is complete, however the weekly data collection employed should ensure that coverage is good. Table 1 provides descriptive statistics for the @ACSnewsfeed Twitter dataset thus obtained.

The 14007 tweets recorded contained a total of 220491 words. It can be seen that the volume of both tweets from, and mentions of, the ACS have varied over time. The ratio of mentions to tweets has varied from more than 2:5.1 to nearly 5:1, suggesting that the ACS achieves a significant level of online interactivity and engagement via Twitter, garnering, on average, multiple mentions by others for every tweet sent. Figure 1 shows the MDS visualisation of tweet text content from the @ ACSnewsfeed account during the period 1 September 2013 – 31 August 2014.

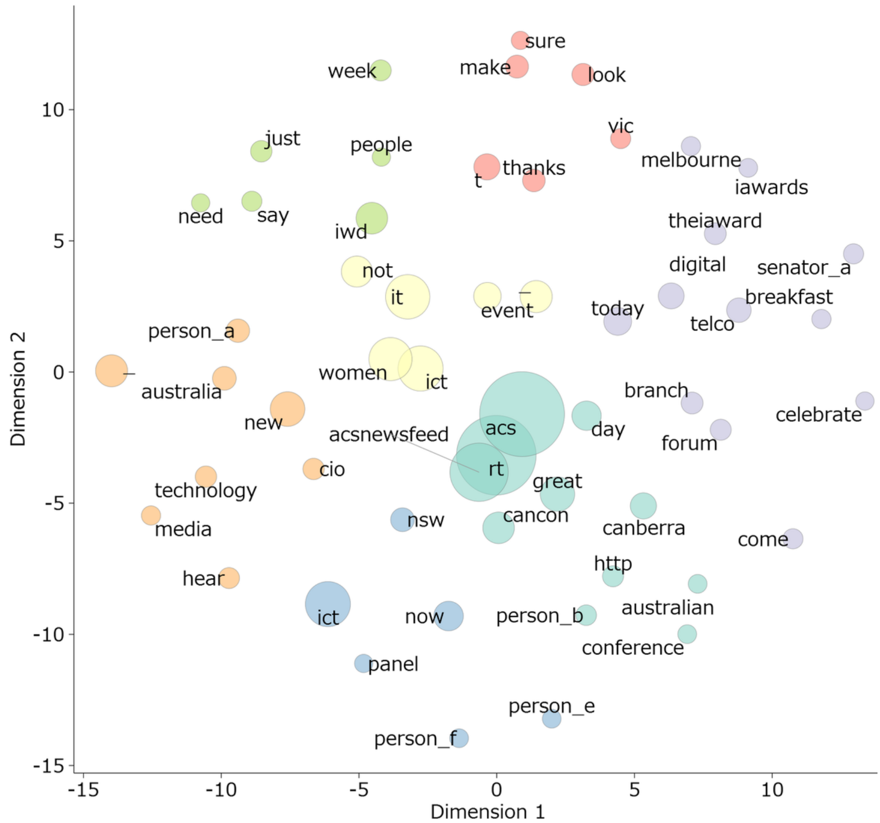
Within individual MDS plots, the relative size of the bubbles provides a comparison of the relative frequency of occurrence of terms. However, this comparison does not hold between MDS plots, as each is based on different numbers of tweets. The MDS visualisations include an indication of clustering of terms using different bubble colouring - the clustering is based on the adjacency of terms when mapped to the two-dimensional plot space, and is indicative only. Key features apparent in Figure 1 include:

- At the upper right, mention of the 2014 iAwards (Australian ICT industry awards night) that was held in Melbourne can be seen;
- At the right is mention of 'senator_a' who was the guest speaker at an ACS event;

Table 1. Descriptive statistics for the @ACSnewsfeed Twitter data set used here

Period	Tweets From ACS	Mentions of ACS	Annual Total
A) 1 September 2013 – 31 August 2014	787	2056	2843
B) 1 September 2014 – 31 August 2015	688	1956	2644
C) 1 September 2015 – 31 August 2016	1189	3350	4539
D) 1 September 2016 – 31 August 2017	692	3289	3981
Totals	3356	10651	14007

Figure 1. MDS plot for tweet content from @ACSnewsfeed 1 September 2013–31 August 2014



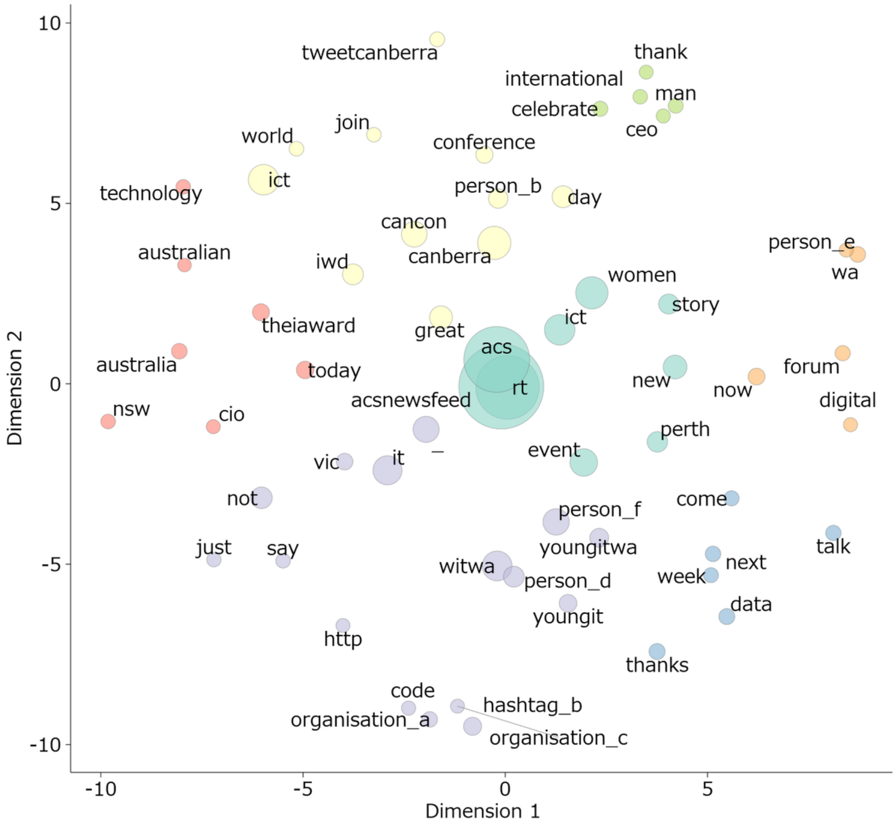
- At the mid-right is a group of terms referring to a Canberra branch digital leadership forum;
- At the lower right there is an invitation to come to the 2013 Canberra 'CanCon' ACS conference, at which 'person_b' was a guest speaker;
- At the bottom, 'person_e' and 'person_f' were regular participants/tweeters at ACS events, including the same events, leading to them being located close together in the plot;
- At the inner top left, a group of terms ('iwd', 'women', 'it', 'ict') relates to celebrating the 2014 International Women's Day.

Figure 2 shows the MDS visualisation of tweet text content from mentions of the @ACSnewsfeed account during the period 1 September 2013 – 31 August 2014.

Key features apparent in Figure 2 include:

- 'perth' (the capital of Western Australia) appears at the mid-right, surrounded by a number of term groups related to Perth and Western Australia;
- At the right, 'person_e' was active (and was retweeted) at a Western Australian ('wa') forum;
- 'person_f' is WA-based, active in ICT, active on Twitter, and presented at an ACS event;
- At the mid-bottom, 'person_d' is WA-based, active in ICT, and active on Twitter;
- 'ICT Women in Perth' is an online journal mentioned by @ACSnewsfeed and was frequently retweeted;
- Women in Technology ('witwa') and 'youngitwa' are WA-based organisations;
- 'hashtag_b' refers to a Perth coding-related event supported by organisation_a and organisation_c;
- At the mid-left, the 2014 iAwards are mentioned ('theiaward');

Figure 2. MDS plot for tweet content about @ACSnewsfeed 1 September 2013–31 August 2014



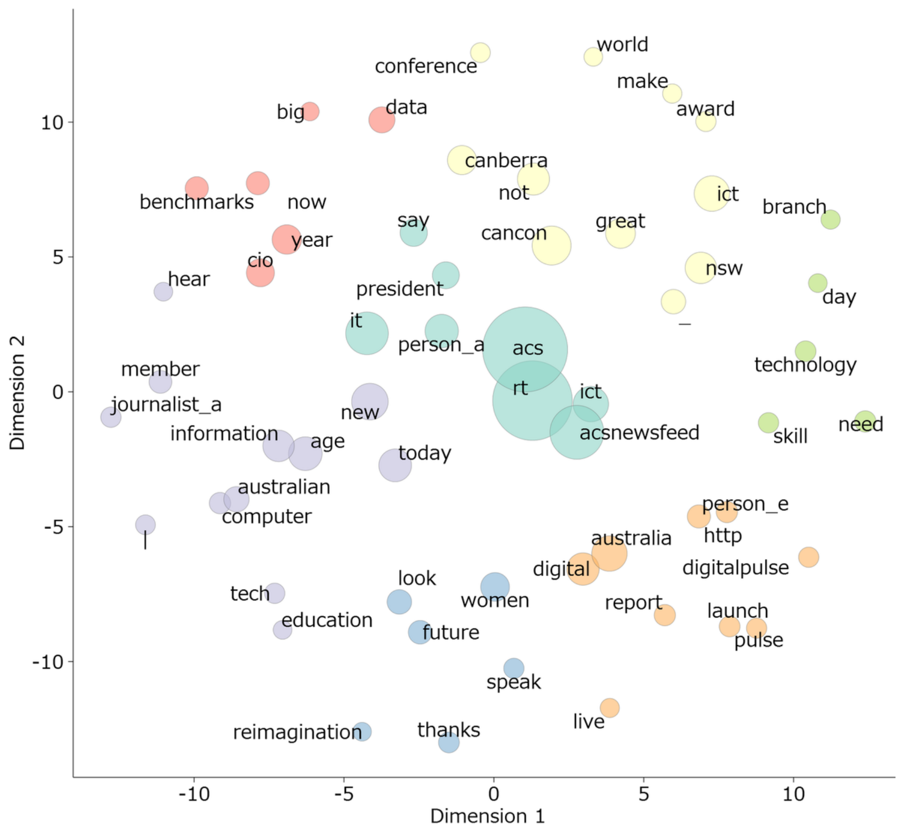
- Nearby, the 2014 International Women's Day is identified ('iwd');
- At the top, from centre out, there is a range of terms related to 2013 CanCon, including 'person_b';
- At the top right, there is a compact cluster related to thanking men in celebrations for IWD.

Terms/items mentioned relatively frequently in tweets from @ACSnewsfeed and in tweets by third parties mentioning @ACSnewsfeed, and hence appearing in the respective MDS plots, include: the iAwards industry awards event, the CanCon Canberra conference – including guest speaker 'person_b', 'person_f' (a regular tweeter participating in ACS activities), and, International Women's Day. There is a significant level of congruence between the terms and term groups present in the two plots. There are also differences in the two MDS plots. Figure 2 shows a number of terms related to Western Australian ACS activities, suggesting a very active ACS affiliated Twitter community in Western Australia. Figures 1 and 2 also illustrate the feature of MDS plots where terms that are shared by different term groups, such as 'canberra' in Figure 1 and 'perth' in Figure 2, are likely to end up positioned between the term groups that they have a common association with.

Figure 3 shows the MDS visualisation of tweet text content from the @ACSnewsfeed account during the period 1 September 2014 – 31 August 2015. Key features apparent include:

- At the lower right, the launch of 2015 Australian Digital Pulse report is mentioned, with which 'person_e' was associated;
- At the mid-left, the phrase "today on information age" can be seen – Information Age is the ACS online news website, with which 'journalist_a' is associated;

Figure 3. MDS plot for tweet content from @ACSnewsfeed 1 September 2014–31 August 2015



- At the top left, there is an announcement of the "CIO of the Year" at the Australian ICT industry 2015 Benchmark Awards night;
- At the mid top and outwards, the 2014 CanCon conference is mentioned, including the topical theme of 'big data'.

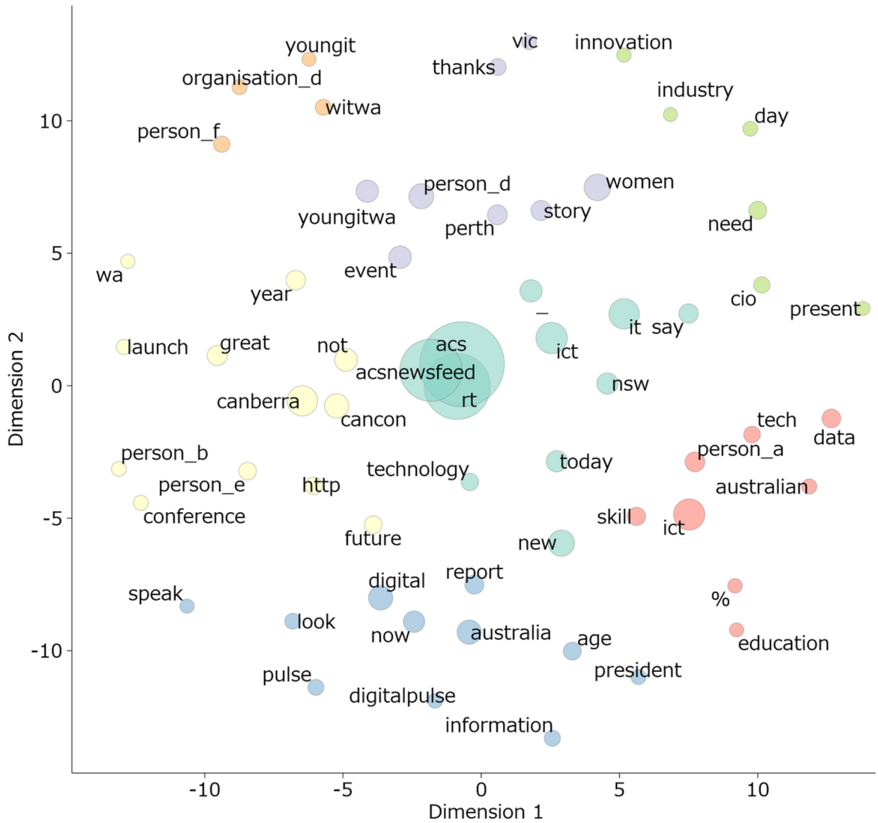
Figure 4 shows the MDS visualisation of tweet text content from mentions of the @ACSnewsfeed account during the period 1 September 2014 – 31 August 2015. Key features apparent include:

- At the bottom, mention of the ACS online news website Information Age can be seen;
- At the left, 'person_b' and 'person_e' are tweeting about the 2014 CanCon conference;
- At the top left, there is a group of terms previously noted as associated with the ACS in Western Australia – 'perth', 'witwa', 'youngitwa', 'person_d' and 'person_f', also 'organisation_d' was associated with a number of WA ACS events.

Figure 5 shows the MDS visualisation of tweet text content from the @ACSnewsfeed account during the period 1 September 2015 – 31 August 2016. Key features apparent include:

- Generally, this MDS plot is spread out with more limited obvious clustering of terms;
- At the right, 'senator_b' participated in the ACS-hosted 2016 Innovation Debate on national ICT policy;

Figure 4. MDS plot for tweet content about @ACSnewsfeed 1 September 2014–31 August 2015



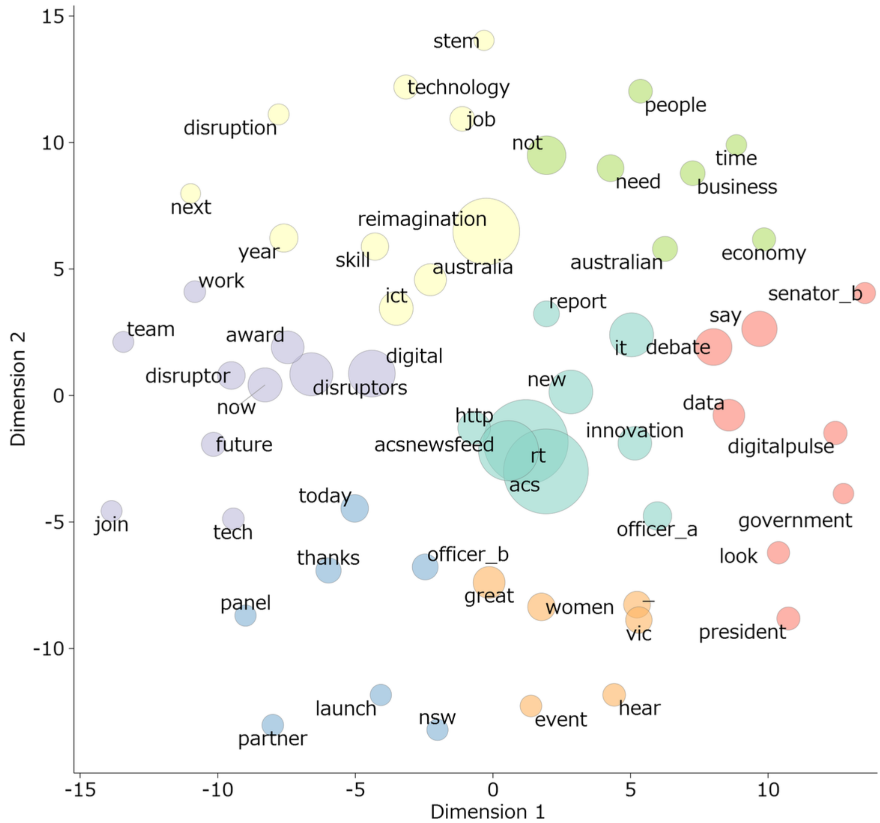
- At the lower left, ‘officer_b’ was an ACS office bearer who noted many ‘thanks’ via Twitter to various ACS supporters/contributors;
- At the left, the 2106 ACS Digital Disruptor awards event is noted;
- At the mid-top, the ACS Reimagination 2015 summit appears with a relatively large term bubble.

Figure 6 shows the MDS visualisation of tweet text content from mentions of the @ACSnewsfeed account during the period 1 September 2015 – 31 August 2016. Key features apparent include:

- At the right, ‘presenter_c’ thanked the ACS for “the opportunity to talk to a room of bright young minds”;
- At the top, mention of the 2016 ACS Digital Disruptor awards can be seen;
- At the inner left there is mention of the ACS Reimagination 2015 summit, again with a relatively large bubble;
- At the inner left, the 2016 Innovation Debate is mentioned;
- At the bottom, the 2015 CanCon conference is mentioned, and also the regular tweeter ‘person_b’.

Figure 7 shows the MDS visualisation of tweet text content from the @ACSnewsfeed account during the period 1 September 2016 – 31 August 2017. Key features apparent include:

Figure 5. MDS plot for tweet content from @ACSnewsfeed 1 September 2015–31 August 2016

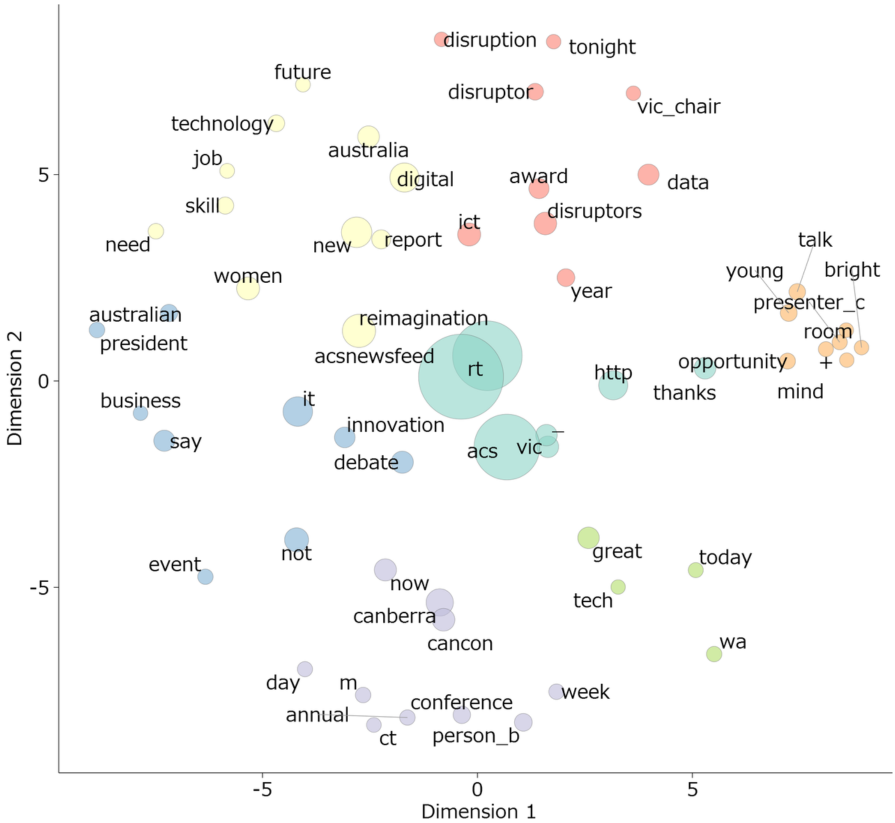


- At the lower right, the launch of the 2017 Digital Pulse report by Deloitte Access Economics (Twitter account @d_accessecon) is mentioned;
- At the lower left, the Reimagination'16 summit is mentioned, along with the associated terms 'innovation', 'technology', 'job' and 'future';
- At the inner left mention of the ACS online news website Information Age can be seen;
- In November 2016 the ACS mounted a range of information videos on YouTube, and each addition generated a tweet of the form "I added a video to a @YouTube playlist …";
- At the top is a group of terms associated with the 2017 ACS Digital Disruptors awards, including thanks to the sponsors of a range of awards ('service transformation', 'skills transformation' and 'consumer services'), as well as congratulations to award finalists and winners;
- At the top right, the 2016 ACS Diversity Summit is identified.

Figure 8 shows the MDS visualisation of tweet text content from mentions of the @ACSnewsfeed account during the period 1 September 2016 – 31 August 2017. Key features apparent include:

- At the lower right, the ACS online news website Information Age is mentioned, along with a heavily retweeted story about plans for AI-based robot police in Dubai;
- At the lower centre, mention of the 2017 ACS Digital Disruptors awards is visible;
- At the lower left are terms related to the 2017 Digital Pulse report (by @d_accessecon), including the theme that "we need more women in STEM jobs";

Figure 6. MDS plot for tweet content about @ACSnewsfeed 1 September 2015–31 August 2016



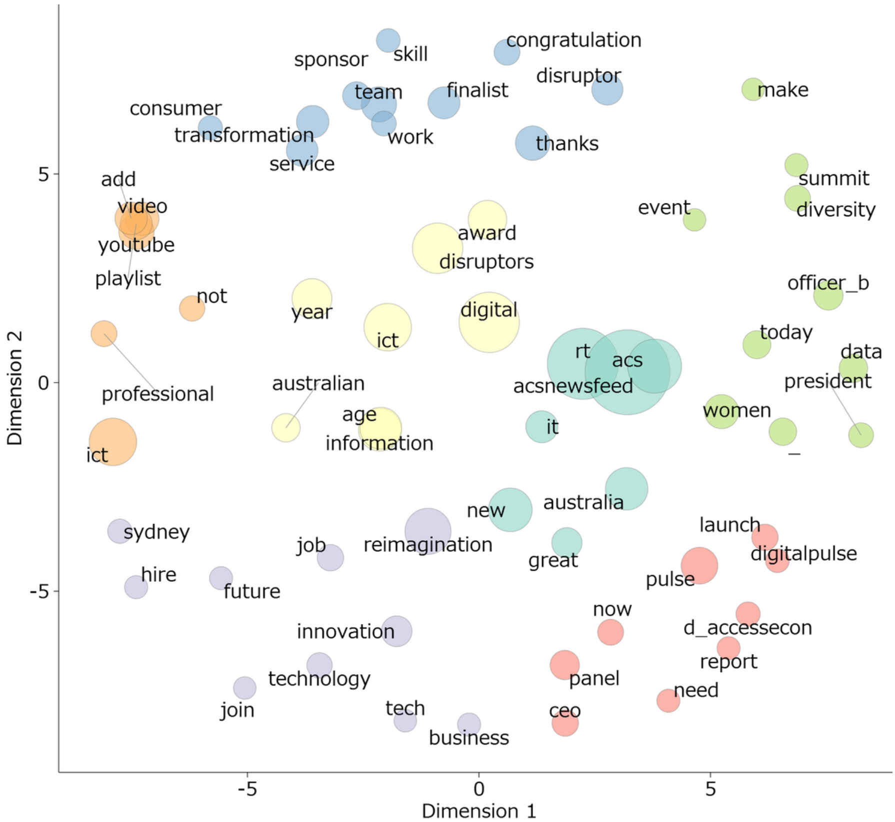
- At the inner top, the Reimagination'16 summit in mentioned, including a panel presentation on 'innovation', and discussion of 'cybersecurity';
- At the top, 'presenter_c' is visible announcing that they are looking forward to presenting at an ACS event on the topics of 'cyberrisk' and 'data breaches'.

General Discussion

All of the 'from' MDS plots (Figures 1, 3, 5 and 7) contain a large, central 'rt' bubble, indicating that the @ACSnewsfeed account is regularly retweeting the tweets of others. All of the 'mention' MDS plots (Figures 2, 4, 6 and 8) contain large, central bubbles naming the ACS and their Twitter account, and 'rt', indicating the frequent sharing of ACS tweets by its followers and other third parties. There is a significant level of congruence between the terms and term groups present in the MDS plot pairs for given time periods, suggesting that the ACS and their online followers on Twitter are interacting around a common set of themes, and is indicative of a large scale social media 'conversation'. The text analytics visualisation method brings key terms and term groups in the Twitter data to the fore, highlights lexical associations between them, and, in some cases, produces phrases that are almost readable in a summary form. It serves as a useful method to visually summarise the tweet text content of potentially large volume of Twitter data, and to show those topics in which the ACS and its Twitter followers have a common interest.

While there is significant congruence between the MDS plot pairs for a specific time period, there are also some differences observed in the terms visible – the Twitter audience, while mentioning the

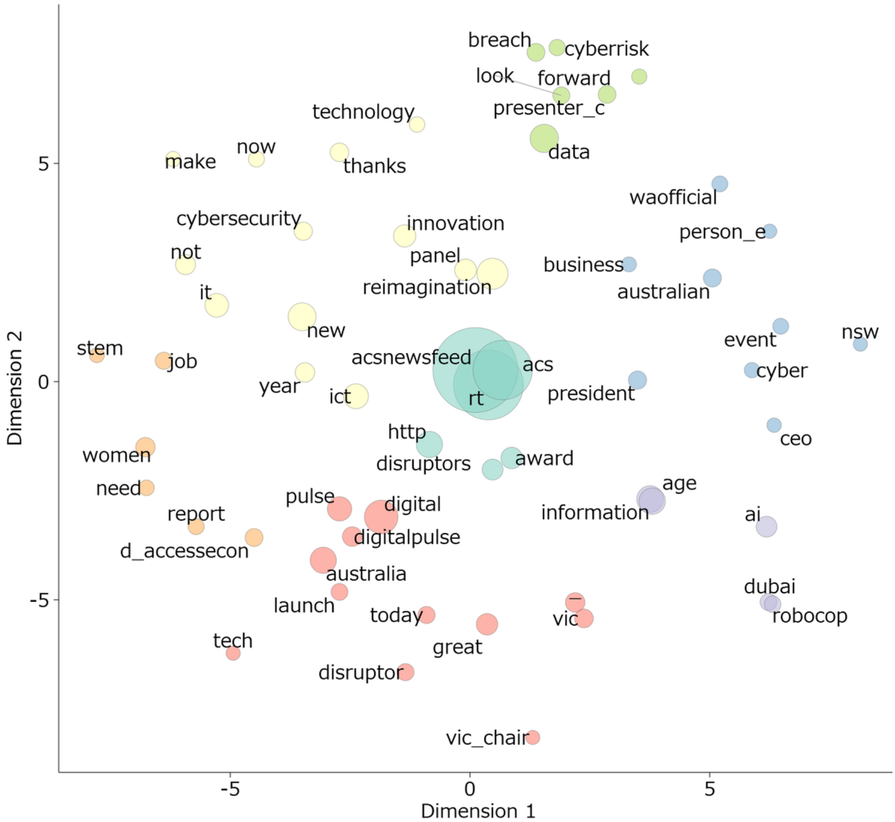
Figure 7. MDS plot for tweet content from @ACSnewsfeed 1 September 2016–31 August 2017



ACS, is also talking about other issues that do not feature in the corresponding ACS visualisations. Such mentions are commentary or discussions on Twitter about the ACS by third parties. Social media can amplify (both positively and negatively) the impact of such conversations about an organisation between stakeholders (Alfaro et al., 2013; Culnan et al., 2010). Such conversations occur continuously, whether the organisation is listening or not, and can be an influential form of marketing. On Twitter, such mentions are also ephemeral, so if an organisation wants to be aware of how it is being referred to in the Twitter environment, it is obliged to monitor such conversations on an on-going basis, otherwise they will be lost if not captured in near real-time. At the time of writing, The ACS Twitter account had more than 5900 followers, and the results here, and previously (Palmer, 2017), show that @ACSnewsfeed account generates multiple mentions for every tweet sent. The presence of a substantial, active and dynamic social media audience requires organisations to respond strategically (Alfaro et al., 2013; Colley, 2014), including professional associations (Gallagher et al., 2016), if they are to derive the maximum value from efforts in social media communication, and if they are to have an awareness of how they are being portrayed on social media by third parties.

In the MDS visualisations, it is apparent that physical ACS events are frequently mentioned in the social media domain – e.g., iAwards, CanCon, Innovation Debate, Digital Disruptor Awards, Reimagination Summit, Diversity Summit, etc. Social media can be a powerful adjunct to discrete physical events such as concerts and conferences, directly contributing to their level of perceived success (Bennett, 2012; Osborne, 2011). Social media can extend the reach of live events to those not able to be physically present (Sopan et al., 2012), and some event organisers actively plan for social media activity, including 'tweet seats' for designated social media reporters, or developing dedicated

Figure 8. MDS plot for tweet content about @ACSnewsfeed 1 September 2016–31 August 2017



event apps to engage their audience during the event (Bennett, 2012). Twitter is often viewed as a desirable social media channel for live events due to its quick, informal nature, its relatively high level of use by the general population, that it automatically creates a time-stamped archive of tweets that can be matched up against temporal aspects of the physical event, and that third-party tools exist for real-time monitoring and retrospective analysis of event-tagged tweets (Osborne, 2011). Apart from the large, central bubbles that generically refer to the ACS in all the MDS plots, and accounting for the different scales in all the MDS plots, the next largest term bubbles are related to the Reimagination 2015 summit, both in Figure 5 (from the ACS) and in Figure 6 (to/about the ACS). In a separate study of Twitter data related to the ACS, over a different multi-year time period, including 2015, it was found that the tweets recorded on a single day, and which were related to the Reimagination 2015 summit, contributed more than seven per cent of all Twitter activity during that period (Palmer, 2017). Here, as previously, it is clear that key physical ACS events, such as conferences, are associated with particularly high levels of Twitter activity and conversation. The virtual is closely linked to the physical, and their overall impact is potentially most powerful when strategically used in conjunction.

The concept of visualising social media 'conversations' on Twitter is not unique. Previous approaches have used network analysis to show the connections between users associated with specific events or topics (Hansen et al., 2011; Pearce et al., 2014). Indeed, the Twitter network connections between the ACS and its stakeholders have previously been studied in detail, but not in the context of understanding social media conversations (Palmer, 2017). Java et al. (2007) note that determining an individual Twitter user's intention is problematic, and that it may be more practical to consider the behaviour of groups of users in aggregate. Here this summative approach to analysis, and overview visualisation, of large sets of Twitter data was taken. Attempts have been made to study the congruence of Twitter conversations between small groups of users over short time frames (Honeycutt & Herring, 2009). Here, using a large-scale, extended duration data set, a more qualitative and holistic method for visualising the themes in, and level of congruence of, Twitter posts by the ACS and its audiences was developed. This new method includes elements of previous network-based approaches, in that key stakeholders are identified by name, and aspects of their relationships are captured by their relative positions in the MDS visualisations. Additionally, the new method captures and presents the ephemeral text content of tweets. This new method provides directly useful social media insights for the ACS, but also contributes a novel research method for characterising online conversations on the Twitter social media platform.

CONCLUSION

Social media systems continue to be important for ICT professionals and ICT professional associations, providing new ways to communicate and interact for and with their members and stakeholders (Al-Busaidi, Ragsdell, & Dawson, 2017; Barrett, Davidson, Prabhu, & Vargo, 2015; Colomo-Palacios, Casado-Lumbreras, Soto-Acosta, & Misra, 2014). Evaluation of the operation and impact of social media are not straightforward. Here text analytics was proposed as a method for conceptualising, identifying, capturing and visualising the large scale 'conversations' occurring between a professional association (the Australian Computer Society) and its stakeholders via the Twitter social media platform. Multidimensional scaling was applied to annual subsets of a four-year data set for the ACS. While there was a significant level of agreement observed between the terms present in the annual pairs of MDS plots, there were also some themes present in the visualisations of the tweet text of the Twitter audience of the ACS that were different to the messages broadcast from the ACS. As in a previous analysis, it was found that prominent features in the Twitter data set related to live events hosted by the ACS, indicating again the important relationship between online/social and real-world physical events. The new method proposed here offers a novel way for organisations, including professional associations, to visualise the large-scale, ephemeral, text conversations relating to themselves on Twitter. It will assist with key strategic uses of social media, including quantifying the scale of activity, and characterising the nature and level of congruence in social media conversations with their stakeholders. While the context presented here was Australian, the organisation and function of the national ICT professional association is the same as in many other countries, and the nature of ICT practice is even more universal, so the application and findings presented should be widely transferable to many other jurisdictions.

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