Tweet to learn: Expertise and centrality in conference Twitter networks

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Abstract

As Twitter use at academic conferences becomes the norm, this discussion backchannel provides attendees with the opportunity to learn from others engaged in tweeting information immediately relevant to the conference. This study uses social constructivist and connectivist learning theories to examine the role of more knowledgeable others (MKOs) in learning networks, and asks how the positions they occupy in the social network allow them to share knowledge. To examine their role, social network analyses were conducted on Twitter network data collected from the Learning Analytics and Knowledge Conference 2014. Findings indicate that more knowledgeable others occupy highly central positions in the network, and that these positions allow them to effectively provide attendees with access to their expertise and knowledge.

1. Introduction

Conferences are an opportunity for like-minded individuals to exchange information, make interpersonal connections, learn, and foster a robust dialogue that contributes to knowledge development in an academic field. One immensely popular and successful use of Twitter, a social networking service that provides users with the opportunity to publish 140 character public messages called tweets, is as a communication backchannel during conferences [3, 8, 22, 23]. This Twitter backchannel provides visibility for commentary on conference activities as well as for the individuals contributing to the conversation. This combination of content and actors has the potential to foster community development during conferences, but can that community be operationalized to form a learning environment for those who participate? Using social constructivist and connectivist learning theories as a framework, this paper examines whether and how conference Twitter networks can facilitate learning.

2. Twitter networks

Twitter communication networks are formed through the use of several popular conventions. Common conventions include: Retweeting, the practice of sharing another user’s tweet to one’s network; Mentions and Replies, a public form of addressing and direct communication with other users; and Hashtags, shared keywords preceded by the ‘#’ hashtag symbol which enable collocation of all tweets using the same keyword. While many conventions are used and understood by the entire Twitter user-base, others may appear for only some sub-communities that develop and integrate them into own communication practices [11]. Users customize their receipt of tweets by Following other users, and by seeking relevant tweets through hashtags. Users primarily interact with those they Follow [16]. Twitter users do not need permission to Follow other users and reciprocation is not required, making many Twitter following connections asymmetric [11]. However, while formal relationships are not always reciprocated, users form communities and groups around common interests or activities [11], which are often characterized by the formation and use of specific hashtags. The primary
way in which conference attendees connect and form communities using Twitter is through the implementation of conference hashtags. Since hashtags can be created by anyone, official conference hashtags are typically created and promoted to reduce potential inconsistencies [23]. Attention to and use of conference hashtags can provide a channel through which latent ties based on conference attendance can become weak ties of acquaintance and interaction with other attendees [15].

2.1. Tweeting at conferences

Motivations for using Twitter are diverse. People use Twitter to talk about daily activities, seek and share information [18], enhance social presence [5], and form and support communities [11]. Research addressing two aspects of Twitter-use informs the current study: research on Twitter use at conferences, and research on Twitter use for fostering learning.

As a popular conference activity, various aspects of Twitter use at academic conferences have been explored in previous research. These studies can be grouped into three types of studies: patterns of Twitter use [3, 22, 26]; information flow through Twitter [20, 21, 28]; and on and off site community development [6, 8, 23].

2.1.1. Patterns of Twitter use at conferences. Patterns of conference Twitter use have been identified by analyzing tweets [3, 26] and by surveying attendees [22]. Chen [3] analyzed tweets from seven conferences for descriptive characteristics, discourse, and social network structures. He found that most of the tweets came from 20% of the users, suggesting that peripheral participation is the main form of contribution. Conversations on Twitter mirrored concurrent conference activities, e.g., more tweets were posted during keynotes and presentations than at other times. He used social network analysis to identify common roles of those tweeting. “Engine participants” posted frequently and attracted a lot of attention when they posted; they often occupied social network hub positions in the network, i.e., highly connected members who have many direct relationships in the network. These actors were also found to be domain experts. “Pop stars” only posted a few times, but garnered a lot of attention. “Lonely tweeters” gained little attention; Chen suggests this is possibly because they were unestablished scholars. “Peripheral players” posted or retweeted infrequently, and may read a lot of tweets but rarely participate [3].

Reinhardt et al. [22] surveyed conference attendees to explore how they perceived Twitter use. The authors found that most respondents viewed Twitter as a useful tool for discussion, dissemination and sharing of ideas, discovery of communities or discussions previously missed, as well as a way to build ties in communities. While most respondents had a positive view of Twitter, the most common negative view was that Twitter was a distraction.

2.1.2. Information flow. One of the primary uses of Twitter during conferences is to share information [3, 22, 26]. Information sharing through Twitter has been tracked using citation analysis as a framework [21, 28]. Weller et al. [28] found that, similar to formal citations, tweets could disseminate scientific information through URLs and retweets. Tweeters also frequently shared journal articles and presentation slides. Retweets in both conferences examined by Weller et al. were over 20% of the total tweets. Tweets containing original content and URLs were more likely to be retweeted than other tweets.

Priem and Costello [21] focused on frequent academic tweeters. They found that their tweets contained a high amount of links to peer reviewed resources, or links to blogs or articles that cited peer reviewed resources. This work suggests that citing through tweeting is considered to be a part of an ongoing dialogue as well as a curatorial process.

Letierce et al. [20] captured conference tweets to examine how users shared information using Twitter. The authors archived tweets from three conferences and classified tweeters as hubs (users who used @mentions) and authorities (those who were @mentioned). They found that tweeters who were both hubs and authorities tended to be at the event and to have authority in the community. Similar to other findings [21, 28], Letierce et al. [20] found that blog posts, slides, and publications were the most popular types of hyperlinked content tweeted during conferences.

2.1.3. On and off site community development. Ebner and Reinhardt [6] used conferences as an example of how Twitter can foster community development during a live event. Tweeters often discussed keynotes and presenters, as well as ideas and concepts from the presentations. Twitter users exchanged a variety of information types including links to resources such pictures or webpages, social and work activities, conference announcements, and feedback and questions. Ebner and Reinhardt concluded that Twitter was used as an alternative communication platform, described by others as a backchannel, to foster community development.

A backchannel is an informal and secondary form of communication that occurs simultaneously with formal communication [23]. Backchannels can decrease feedback lag while encouraging participation, interaction, and the collective construction of understanding [3]. In their examination of the
effectiveness of Twitter as a form of backchannel communication, Ross et al. [23] found that Twitter activity consisted of multiple, discontinuous, dialogues between users. Over half of the tweets mentioned other users, indicating conversational and collaborative practices by tweeters. Sharing resources through hyperlinks was also commonly practiced and served as a way to provide extended information on a topic. Content analysis revealed that most tweets served the function of jotting down notes from the front channel of communication, which mirrors findings by Vega et al. that the majority of tweets contributed during a conference were observations of conference happenings [26]. However, Ross et al. [23] suggest that observational tweeting indicates that attendees were using Twitter to share experiences and, to a degree, co-construct knowledge. The next most common function of tweeting was to develop discussion networks, thereby enhancing participation and engagement with conference activity.

While Ross et al. [23] examined the utility of a Twitter backchannel for those attending conferences, Ebner, Mühlburger, et al. [8] examined the potential for Twitter as a backchannel for those unable to attend the conference. To examine the efficacy of Twitter as a conduit of information for non-attendees, Ebner, Mühlburger, et al. [8] monitored tweets from an “unconference.” However, they found that over half of the tweets were irrelevant, and only 10% were topical discussions. The study concluded that due to a lack of context and the high number of retweets which also lacked context, it would be difficult for followers not attending the conference to follow the conversation. The relatively unstructured nature of an un-conference, which did not provide a scheduled program with specific workshop topics or talk titles, is perhaps not an ideal choice of focus for a study looking to examine the use of Twitter by those who were not in attendance.

The studies above show Twitter as a useful tool for facilitating exchange and dialogue at conferences. Twitter use at conferences is generally the result of a relatively small subgroup of attendees, using Twitter to share experiences, information and resources relevant to conference happenings and topics. The use of Twitter as a backchannel during conferences fosters community development, and enhances participation and engagement with conference activity.

2.2. Twitter and learning

Research has also been conducted on the use of Twitter as a tool to facilitate learning. Influenced by social constructivist learning theories, Ebner, Leinhardt, et al. [7] hypothesized that the continuous and transparent communication afforded by microblogging could be used to facilitate informal (i.e., experiential) and process-oriented (i.e., self-managed, research-based) learning. Ebner, Leinhardt, et al. tracked students’ posts over the course of one semester. Analysis revealed that Reply posts were the most common, indicating that students and instructors were communicating and that the process likely helped students understand their subject. High proportions of private messages suggested that students engaged in discussions with no restraints and created increased opportunities for informal learning. Ebner, Leinhardt, et al. [7] concluded that microblogging could support process-oriented learning by providing constant and transparent information flow between students and instructors, thus offering great potential to expand teaching and learning beyond the classroom.

Dunlap and Lowenthal [5] argued that an important aspect of informal learning is the ability to engage in just-in-time interactions. These help strengthen interpersonal relationships that bond the learning community and help students become more engaged in learning activities. They proposed that Twitter could be used to facilitate informal communication outside a classroom setting, and enhance students’ social presence. In their experience, they found that Twitter allowed students to quickly access information, write for an audience, write concisely, connect with communities of practice, participate in informal learning, and maintain relationships.

Gao et al. [9] analyzed published studies examining the use of Twitter in learning environment to identify the educational benefits that microblogging may have on teaching and learning. Across studies, benefits were found associated with: the opportunity for students to communicate with a wider audience and to learn outside the constrained space and time of formal classroom settings; the ability to document “just-in-time” and reflective thoughts; the potential to review discussions and content shared via Twitter; and enhanced social learning grounded in social constructivism such as interactive activities, informal learning, and the formation of learning communities [9]. Drawbacks included lack of familiarity with the technology, information overflow, and unequal participation. However, despite these drawbacks, Gao et al. [9, p. 794] conclude that Twitter and other microblogging platforms provide “immense opportunities to extend learning beyond the classrooms and blur the line between formal and informal learning.”

2.3. Learning theories for Twitter

As a social medium, dependent on posting and response by members of a community, models of
learning for Twitter draw from social perspectives, such as social constructivism and connectivism [see also 2].

Social Constructivism is a perspective that views learning as the shared creation of meaning, and knowledge as created iteratively by learners as they interpret and make sense of their experiences. This perspective emerged from the work of Vygotsky [27] who argued that all cognitive functions derive from social interactions. His work views learning as a process of integration into a knowledge community that can consist of individuals with various perspectives based on their own subjective experiences. Knowledge is constructed through the processes of sharing perspectives and negotiating meaning in these resulting communities of practice.

Connectivism views learning as negotiation and construction of knowledge across a network of learners, technologies, and information sources [24]. Thus, connectivism is well suited to looking at how people learn in a networked, technology-enabled information society. Learners develop interconnectedness across a variety of environments, and make sense of knowledge fragments within a large pool of collective knowledge. Learning becomes less about ‘know-what’ and ‘know-how,’ and more about ‘know-where,’ emphasizing the importance of finding access to good information sources, and connecting accurate, up-to-date bits of knowledge together in a sensemaking process.

3. Theory & hypotheses

Previous research supports the idea that Twitter can be used to facilitate learning through social constructivist based learning scenarios [5, 7, 9]. But what is social constructivism? Social constructivism is associated with the epistemology interpretivism, which states that reality is internal and knowledge is constructed [24]. Therefore, social constructivist learning theory is centered on learning through building knowledge with peers. Knowledge building transpires through engaging in meaningful tasks. During these tasks learners work within communities to co-construct knowledge and create meaning. In learning environments students are exposed to what Vygotsky [27] refers to as the Zone of Proximal Development (ZPD). ZPD is “the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance, or in collaboration with more capable peers” [27, p. 86]. A vital element of the ZPD is interaction and engagement with more knowledgeable others (MKOs) because they offer the expertise and potential modelling for learners to reduce the distance between what learners know and what they can learn from interaction with MKOs. MKO refers to anyone who has a superior understanding or further developed ability level than the learner. In our research, which focuses on academic conferences where the community consists primarily of experts and experts-in-training, we believe that MKOs would be highly cited researchers and experts who are active leaders in their fields.

To account for the impact of technology and underlying social changes, connectivism emphasizes the importance of making and forming connections and recognizing patterns. Some principles of connectivism include learning through diversity of opinions; making connections between fields, ideas and concepts; maintaining currency; and learning through decision-making [24]. From this perspective, communities are of utmost importance to learning: Since we cannot experience everything, other people’s experiences, and hence other people, become the surrogates for knowledge. ‘I store my knowledge in my friends’ is an axiom for collecting knowledge through collecting people [24].

To understand and evaluate learning in a particular environment, social network analysis (SNA) can be used to identify people who maintain and foster knowledge flow. Similar to MKOs in Vygotsky’s ZDP, information hubs in social networks can facilitate knowledge flow to those within a learning community and foster the process of connection making and knowledge acquisition. If Twitter networks at conferences are indeed learning environments, then we would expect that MKOs would be hubs in the network.

Hubs can be defined by their position in the network. In SNA, hubs are nodes with high centrality measures, and high levels of prestige (i.e., generally have many mentions and retweets, or ‘in-links’). Using Chen’s [4] findings as reference, we expect that MKOs are likely to be ‘Pop Star’ type actors in the network, having fewer posts but more attention paid to them.

This leads to the following four hypotheses:

**H1**: MKOs will have high levels of centrality in the network.

**H2**: MKOs will have high levels of prestige in the network.

**H3**: MKOs will tweet less frequently than others.

**H4**: MKOs will be frequently mentioned in tweets.

4. Research design

Previous research on tweeting during conferences has examined tweets from single conferences [6, 7, 25] and multiple conferences [3, 20, 22, 23, 28]. As an
exploratory study, we opted for a case study approach as case studies are used to explore an event in depth [4]. The conference we selected was the Learning Analytics and Knowledge (LAK) Conference 2014. The conference took place in Indianapolis, Indiana between March 24 and March 28. LAK is in its fourth year and brings together a community of participants involved in defining and building knowledge around the emerging field of learning analytics. We chose LAK14 for the following reasons: first, attendees would likely be technologically adept and therefore likely to use Twitter; second, attendees are likely to be experienced using technologies in learning environments, and therefore may be more likely to use Twitter for learning purposes; third, in his analysis of tweets from LAK11, Chen [3] found that instances of retweets and messages were high in comparison to other conferences, suggesting that Twitter use by LAK attendees is more interactive in comparison to other conferences; fourth, as the representative conference of an emerging discipline, the conference is small (under 500 attendees), and so identifying MKOs would be a manageable task; finally, conference organizers provided a list of attendees, simplifying the identification of tweeters in attendance.

4.1. Identifying More Knowledgeable Others

More knowledgeable others (MKOs) can be difficult to identify in an online environment and indicators may vary according to academic discipline or area. However, two common factors may help measure whether or not a person is an MKO. First, is a person highly involved in their community? For example, do they have leadership roles in relevant organizations? Second, has their work been widely disseminated? Have they been published in relevant journals or participate in conferences? Is their work highly cited? Since the focus of the LAK conference is learning analytics, a Tweeter’s status as an MKO in the #LAK14 Twitter network was based on their involvement in the learning analytics field. Two measures of different indicators were used to create a Learning Analytics MKO (LA MKO) score. First, LA MKOs were evaluated according to membership in learning analytics organizations and second, LA MKOs were evaluated according to various levels of involvement in current and previous LAK conferences. Table 1 describes the measures and the point system. For most indicators, if a Tweeter met the criteria he or she was awarded one point. However, for two indicators (executive committee of SoLAR and keynote speaker) two points were awarded because these indicators were considered to be more indicative of prominence and expertise.

Each Tweeter’s LA MKO score was calculated based on the sum of their points. A Tweeter was considered an LA MKO if they received a final score of four or above, an average of one point per indicator. A Tweeter’s status as an MKO in the #LAK14 Twitter network need not be discipline specific. To determine whether or not MKOs from disciplines outside learning analytics (referred to as “Other MKOs”) were tweeting, each Tweeter’s h-index score was recorded. The h-index measures the publication productivity of a scholar based on their most cited papers and the citations they have received in other publications. It is often used as a quantitative measurement of success [12]. While there are a number of criticisms [see 12] of the use of h-index as an evaluation, we considered it to be a useful measurement, as it was anticipated the Other MKOs would be from related fields and thus cross-disciplinary citation practices would have little effect. Additionally, h-index would be an indicator of both high rates of citation and prolific publication that are often associated with being an established expert in one’s field.

Table 1. LA MKO measurement.

<table>
<thead>
<tr>
<th>Measures</th>
<th>Indicators</th>
<th>Criteria</th>
<th>Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organization</td>
<td>SoLAR (Society for Learning Analytics Research)</td>
<td>Exec. Committee Member</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Steering Committee Member</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Not a committee member</td>
<td>0</td>
</tr>
<tr>
<td>LASI (Learning</td>
<td>Analytics Summer Institute)</td>
<td>Member of Org. Committee (2013)</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Not a committee member</td>
<td>0</td>
</tr>
<tr>
<td>LAK Conference</td>
<td>Presentations</td>
<td>LAK Presenter (2011-2014)</td>
<td>1 per pres.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Not a presenter</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Keynotes</td>
<td>Keynote speaker</td>
<td>2</td>
</tr>
</tbody>
</table>

A Tweeter was considered an Other MKO if their h-index score was greater than or equal to 23. An h-index score of 23 was chosen based on Iles’ [17] calculation of the average h-index scores on Google Scholar of full professors of Computer Science. H-index data on #LAK14 Tweeters were collected using Google Scholar for consistency.
4.2. Data collection

Tweets were collected using the Twitter Archiving Google Spreadsheet (TAGS) [14]. The TAGS script automatically archives all tweets with a specific search term by saving them into a Google Spreadsheet in real time. The official conference hashtag, #LAK14, was used as the search term. Data collection began March 15 2014, 9 days before the beginning of the conference to include pre-conference buzz, and continued until April 5 2014, 7 days after the end of the conference to include post-conference reflections. 3079 tweets that included the hashtag #LAK14 were collected during the 21 days of data collection.

4.3. Data analysis

Two types of Twitter networks were analyzed: retweet networks and name networks. Retweet networks are based on who retweets whom, where the nodes are tweeters and the ties are the retweeted messages. Name networks are based on who mentions whom, where nodes are both Twitter users and people not tweeting but mentioned on Twitter, and ties are the messages between the original Tweeter and the name or username mentioned. UCINET and NetDraw [1] were used to analyze and graph the Retweet network, and Netlytic [10] was used to analyze and graph the name network.

Three types of network measures were calculated in UCINET: betweenness, eigenvector centrality, and prestige. Betweenness centrality measures the extent to which other actors lie on the shortest path between pairs in the network. Those who have high measures of betweenness are often in positions where they control information flow between actors [19]. Eigenvector centrality is used to identify the most central actors in a network in terms of the overall network [13]. Similarly, prestige is a measure of prominence in a network, but is measured by how often nodes are the receivers of ties; prestige is an indicator of popularity [19]. In the Retweet network, prestige is measured by whose tweets are retweeted the most. To compare the network measures of MKOs versus other LAK Twitter network participants, MKO status was considered an attribute of users.

5. Results

The results are divided into two sections: descriptive statistics and hypotheses. The Descriptive Statistics section provides an overview of tweeting habits of LAK14 attendees and an overview of who in the Twitter network are MKOs. The Hypotheses section responds to each of the four hypotheses proposed in Section 3.

5.1. Descriptive statistics

A total of 352 Twitter accounts tweeted during LAK14. 88 (25%) of those accounts were linked to people who were registered to the conference while 186 (52.8%) of the accounts were linked to people who were not registered. 78 (22.2%) accounts could not be linked to conference attendance because the users did not include their full name in their Twitter biography, or because the accounts did not represent an individual (i.e., the account was created to promote a product (e.g., @Netlytic), an organization (e.g., @GradPurdue), an event (e.g., @lak15marist), or a project (e.g., @HumaBirdProject). 239 people were registered for the conference. Of these registrants, 36.4% tweeted at least once.

Of the 352 Twitter accounts, 16 belonged to LA MKOs and 11 belonged to Other MKOs. 52 of the accounts did not represent an individual person therefore could not be an MKO. 26 of the accounts did not list an identifiable name (e.g., they only used a pseudonym, or a last initial) or the account was inactive or suspended; therefore, these accounts could not be evaluated as MKOs.

5.2. Hypotheses

As retweets have been used as a form of citation analysis [28], and since citation analysis can be used to track both information flow in a network and highlight key contributors, Hypotheses 1 and 2 are tested using the retweet network of LAK14. Hypothesis 4 is tested using the name network.

**H1: MKOs will have high levels of centrality in the network.**

Figures 1 and 2 show two network diagrams of the LAK14 retweet network. Node size is based on centrality measures. Figure 1 shows node size based on eigenvector centrality, and Figure 2 shows node size based on betweenness centrality.

Red nodes represent actors who are learning analytic more knowledgeable others (LA MKOs) and circles represent “other” more knowledgeable others (Other MKOs). Red circles represent actors who are both learning analytic and other MKOs. The eigenvector diagram shows a moderately sized group of highly central actors in the network. Based on the diagram alone, it is difficult to determine if an actor’s role as an MKO has an effect on eigenvector centrality.
Figure 1. Eigenvector diagram of the LAK14 retweet network.

Table 2 contains the results of a t-test conducted to determine if there are significant differences between the two groups.

Table 2. Eigenvector centrality t-tests.

<table>
<thead>
<tr>
<th></th>
<th>LA MKO</th>
<th>Not LA MKO</th>
<th>Other MKO</th>
<th>Not Other MKO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.068</td>
<td>0.014</td>
<td>0.042</td>
<td>0.016</td>
</tr>
<tr>
<td>Std Dev</td>
<td>0.071</td>
<td>0.048</td>
<td>0.079</td>
<td>0.049</td>
</tr>
<tr>
<td>N</td>
<td>16.00</td>
<td>336.00</td>
<td>11.00</td>
<td>341.00</td>
</tr>
<tr>
<td>Diff. in means</td>
<td>0.054</td>
<td>0.027</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Tailed Test</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The average eigenvector score of non-MKOs is 0.054 units less than the average eigenvector of MKOs, and there is a 0.27% chance that the averages are the same. Eigenvector scores of LA MKOs are significantly greater than those who are not LA MKOs. Similarly, the average eigenvector score of non-Other MKOs is 0.027 units less than the average score of Other MKOs and there is a 6.81% chance that the averages are the same. Again, the eigenvector scores of Other MKOs are significantly greater than those who are not Other MKOs, although significance is not as strong. Overall, MKOs are more likely to have high centrality in a network than non-MKOs.

Figure 2. Betweenness diagram of the LAK14 retweet network.

In the betweenness diagram (figure 2), two actors have noticeably high betweenness scores indicating their role as information conduits (see yellow arrows). One actor is both an LA and Other MKO, while the other is neither. The latter actor was involved in organizing the conference and was a prolific Tweeter during the conference. Table 3 contains the results from the t-test conducted to determine if betweenness centrality is higher for MKOs than non-MKOs.

Normalized betweenness scores were used for the t-tests since the betweenness scores for the LAK14 network were very high, suggesting a network that relays high volumes of information within and beyond the immediate network. This is largely due to the betweenness centrality of the MKO members. For example, the mean non-normalized betweenness score for LA MKOs is 864.62, and the mean non-normalized betweenness score for those who are not LA MKOs is 86.753.

Table 3. Betweenness centrality t-tests. (normalized)

<table>
<thead>
<tr>
<th></th>
<th>LA MKO</th>
<th>Not LA MKO</th>
<th>Other MKO</th>
<th>Not Other MKO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.704</td>
<td>0.071</td>
<td>0.688</td>
<td>0.080</td>
</tr>
<tr>
<td>Std Dev</td>
<td>1.352</td>
<td>0.390</td>
<td>1.627</td>
<td>0.396</td>
</tr>
<tr>
<td>N</td>
<td>16.00</td>
<td>336.00</td>
<td>11.00</td>
<td>341.00</td>
</tr>
<tr>
<td>Diff. in means</td>
<td>0.633</td>
<td>0.607</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Tailed Test</td>
<td>0.0012</td>
<td>0.0059</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Standard deviations were also high, suggesting a lot of variance between the betweenness centrality scores of the actors in each group. The average normalized betweenness score of non-LA MKOs is 0.633 units less than the average betweenness of LA MKOs, and there is a 0.12% chance that the averages are the same. Betweenness scores of LA MKOs are significantly greater than those who are not LA MKOs. Similarly, the average normalized betweenness score of non-Other MKOs is .607 units less than the average score of Other MKOs and there is a 0.59% chance that the averages are the same. Again, betweenness scores of Other MKOs are significantly greater than those who are not Other MKOs. Overall, MKOs are more likely to be information conduits than non-MKOs. MKOs are significantly more likely to have higher eigenvector and betweenness centrality scores. Therefore, H1 is supported.

H2: MKOs will have high levels of prestige in the network.

In-degree centrality was calculated to measure prestige. Table 4 displays the results of the analysis.
Table 4. In-degree t-tests.

<table>
<thead>
<tr>
<th></th>
<th>LA MKO</th>
<th>Not LA MKO</th>
<th>Other MKO</th>
<th>Other MKO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>27.94</td>
<td>2.393</td>
<td>20</td>
<td>3.023</td>
</tr>
<tr>
<td>Std Dev</td>
<td>35.867</td>
<td>10.126</td>
<td>42</td>
<td>11.162</td>
</tr>
<tr>
<td>N</td>
<td>16.000</td>
<td>336.00</td>
<td>11.00</td>
<td>341.00</td>
</tr>
<tr>
<td>Diff. in means</td>
<td>25.545</td>
<td>16.977</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Tailed Test</td>
<td>0.0001</td>
<td>0.0044</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

On average, non-LA MKOs were retweeted 25.5 times less than LA MKO; there is a 0.01% chance that the averages are the same. Similarly, on average, non-Other MKOs were retweeted 16.97 times less than Other MKOs with a 0.44% chance that the averages are the same. Both LA MKOs and Other MKOs are retweeted significantly more frequently than non-MKOs, thus supporting H2.

**H3. MKOs will tweet less frequently than Non-MKOs.**

Of the 3079 tweets in the LAK14 network, 292 (9.5%) were tweeted by LA MKOs and 2756 (89.5%) were written by non-LA MKOs. 152 (4.9%) tweets were tweeted by Other MKOs and 2886 (93.7%) were tweeted by non-Other MKOs. The frequency counts suggest that the vast majority of tweets were written by those without either type of MKO status. However, given the difference in number of MKOs versus the number of Non MKOs, the average tweets per group were compared. On average, the 16 LA MKOs tweeted 18.25 times versus non-LA MKOs who tweeted an average of 8.72 times. The 11 Other MKOs tweeted an average of 13.72 times versus the non-Other MKOs who tweeted an average of 9.1 times. This suggests that proportionally, MKOs tweeted more than Non-MKOs. However, the standard deviations of the number of times LA MKOs (24.16) and Other MKOs (22.7) are high. While MKOs tend to tweet less frequently than Non-MKOs as a whole, some MKOs tweet frequently. Thus, H3 is only partially supported. MKOs status may only partially predict tweet frequency and it is likely that other variables, such as prior tweeting habits and involvement in organizing a conference, are also predictors of how frequently attendees tweet at conferences.

**H4: MKOs will be frequently mentioned in tweets.**

Figure 3 shows the network diagram of name mentions in the #LAK14 Twitter network. Nodes are sized by total degree centrality. A community detection algorithm was used to group members who mentioned each other, or were co-mentioned by others, according to frequency, into color-coded clusters.

In addition to providing network visualizations, Netlytic provides a word cloud of the names tweeted the most frequently.

Figure 4 is a screen capture of the word cloud. The names that are mentioned the most are largest. The total number of times the name was mentioned is in the superscript above the name.

To measure the impact of MKO status on name mentions, the frequency of mentions was calculated and compared to the number of name mentions of non-MKOs using a t-test. Netlytic captured and counted all names mentioned in the LAK14 tweets, including names of people who were not participants in the Twitter network. For example, Netlytic identified names of fictional characters (e.g., Anna Karenina), celebrities (e.g., Dan Ackroyd), nouns (e.g., brain), first/last names only (e.g., Chris and Chang) and members of the learning analytics community who did not tweet (e.g., Carolyn Rose and Roy Pea). Because the focus is on people who tweeted during the conference, all other names were excluded. Counts of variants of the same name (e.g. Dan Hickey, Daniel Hickey, and dthickey) were summed. Table 5 displays the results of the t-test.

On average, LA MKOs were mentioned 39.39 times more than non-LA MKOs and Other MKOs were mentioned 40.22 times more than non-Other MKOs. Both of these differences are statistically significant.
The data indicate that MKOs are more likely to be mentioned in tweets, thus supporting H4.

<table>
<thead>
<tr>
<th>Variable</th>
<th>MKO Mean (SD)</th>
<th>Not MKO Mean (SD)</th>
<th>Mean Difference (95% CI)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>LA MKO Tweets</td>
<td>54.89 (51.36)</td>
<td>15.49 (22.82)</td>
<td>39.39 (24.24-54.37)</td>
<td>p&lt;0.0001</td>
</tr>
<tr>
<td>Other MKO Tweets</td>
<td>55.71 (59.57)</td>
<td>15.49 (22.82)</td>
<td>40.22 (19.47-60.97)</td>
<td>p=0.0002</td>
</tr>
</tbody>
</table>

### 6. Discussion

When analyzing tweeters, Chen [3] identified two types of central participants: pop stars and engine participants. Similarly, Letieerce et al. [21] identified hubs and authorities as important figures in the network. Pop stars, engine participants, hubs, and authorities are members of Twitter communities who provide connections and information within the network. The roles of MKOs in the #LAK14 Twitter network are similar. MKOs tend to have higher eigenvector centrality scores, suggesting that they are highly central hubs of the network. MKOs also tend to have higher betweenness centrality, suggesting that they are authoritative information conduits. Given the high level of variance between tweeting frequencies of MKOs, it is likely that they might play the role of either pop stars who tweet infrequently, or engine participants, who tweet a lot. The high frequency of mentions demonstrated by the name network analysis indicates that whether or not MKOs tweet frequently, they are important and predominant members of the twitter community. The high number of mentions suggests that their contributions to the community — either to Twitter directly, or through other avenues that are then mentioned by others in Twitter — could be considered valued sources of information central to an ongoing dialogue.

In these highly central roles, MKOs have the ability to make impactful contributions to the learning community. As hubs, MKOs are positioned so that their contributions to the community can help reduce the distance between their knowledge and that of learners as described by Vygotsky’s Zone of Proximal Development [27]. Additionally, their central positions within the network can help facilitate connection making. The centrality of Other MKOs suggests that even when a conference or a learning community is discipline-specific, those from outside the discipline can help learners make connections between fields. In the Twitter network, their positions allow both LA and Other MKOs to provide scaffolding as learners identify quality information sources and construct knowledge.

Identifying MKOs in a learning network can have practical implications. While the measurement of what constitutes an MKO is likely to vary by situation, identification of MKOs in a network can highlight who and where key information providers in a network are likely to be. It provides an element of know-where (the ability to find knowledge), which, according to [24] is supplanting know-what and know-how. If learners know where to access knowledge, they can begin to make connections and sensemaking towards learning.

### 6.1. Limitations and further research

The results of this study focus on the quantitative positioning of MKOs in a particular learning network. While the results indicate that MKOs occupy central positions in the network and thus have the ability to make impactful contributions to the community, without a content analysis of their tweets it is unknown whether or not they are taking advantage of their positions and actually providing meaningful content. Further analysis will examine the content of the tweets to determine if and how the content contributes to learning.

Similarly, it is unknown to what extent and in what ways learners are leveraging the contributions of MKOs towards their own learning processes. Further research will focus on how others in the network demonstrate comprehension, application, extension, and reciprocation of the information proffered by MKOs.

Additionally, the study is limited to those who tweeted. The name network analysis indicated that members of the field who did not tweet during the conference were mentioned. It could be that their ideas are impactful even though they did not tweet themselves. Further analysis could extend the coding of MKOs from only Twitter users to all those who are mentioned by conference tweeters.

Finally, Other MKOs were identified using Google Scholar. However, h-index scores are only readily available for those who have a Google Scholar profile; therefore, it is possible that some Other MKOs were overlooked. A more universal or robust means of identifying other MKOs could reduce the possibility that some MKOs were missed.

### 7. Conclusion

Conferences provide attendees with the opportunity to learn in a variety of ways: learning may take place through formal avenues such as listening to speakers, and informal learning may take place during social
interactions and events or through backchannel communications. Social constructivist and connectivist learning theories highlight the importance of working with peers and more knowledgeable others on meaningful tasks to co-construct knowledge, create meaning, and make connections. Discussions through the Twitter backchannel during conferences is one way in which learners can interact with and learn from more knowledgeable others. This study examined the network positions of more knowledgeable others in a conference twitter community and found that they occupied prominent positions in the network. These positions provide them with the opportunity to disseminate knowledge and information. Understanding the roles and positions of more knowledgeable others in learning environments provides insight into the structure of learning networks and demonstrates how the structure may be utilized to further facilitate learning opportunities.

8. References

[17] Iles, F. “What is a good H index for a Professor in Biology compared to a Professor of Psychology?” [Msg 1]. 2013.http://www.researchgate.net/post/What_is_a_good_H_index_for_a_Professor_in_Biology_compared_to_a_Professor_of_Psychology