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Social network analysis of twitter use during the AERA 2017 annual conference

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Abstract
Social network analysis can provide insight into the educational research community as it manifests and evolves online. This study presents a social network analysis of Twitter use during the American Educational Research Association 2017 Annual Conference. The overall social network is sparse with low density, with a few very active nodes and many unconnected Twitter users. Tweets were positive or neutral and rarely negative. Degree of centrality and of closeness of the top 10 users is high, relative to the top 100 users as centrality, closeness, and betweenness taper off quickly. We interpret this as due to the large number of non-intersecting special interest groups that dilute the overall density of the network. Future social network analysis studies should compare SIGs on various metrics and track their developments over time.

Keywords Twitter · Social network analysis · Educational research · Academic conference

1 Introduction

Twitter is one of the most popular social networking platforms today. According to Twitter's latest earnings report, the microblogging website now has about 330 million monthly active users (Twitter 2017). Given the uptake of social networking among

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academics and in academia in general (Williams and Woodacre 2016), it is no surprise that social networking platforms such as Twitter have gained increasing interest and attention as fertile ground for academic research (Tang and Hew 2017).

Reviews of research of Twitter use, or microblogging, in education settings have been conducted for education more broadly (Gao et al. 2012) and for language learning more specifically (Hattem and Lomicka 2016). Twitter use, or microblogging, has the potential to encourage participation, engagement, reflective thinking as well as collaborative learning in varied learning contexts (Gao et al. 2012). In their content analysis of the literature on Twitter use in language learning, Hattem and Lomicka (2016) identified four broad themes in the applications of Twitter to learning: (a) learner autonomy/motivation, community building/development, (b) interaction with native speakers, (c) language skills and (d) competencies, and communication/interaction. For a more general education perspective, Tang and Hew (2017), in examining the empirical literature on Twitter use in teaching and learning, found that Twitter was most commonly used for communication and assessment.

In recent years, Twitter has come to become an important backchannel for academic conferences in various fields (Chung and Woo 2015; Kimmons and Veletsianos 2016; Lee et al. 2017; Parra et al. 2016; Salzmann-Erikson 2017). Conference-specific hashtags can provide important insights about scholarly communication at a conference. According to Parra et al. (2016), "by identifying (i) which are the most popular conference topics, (ii) who emerge as the online community leaders, (iii) how participants interact, (iv) what is the users' sentiment towards the event, etc. organizers and researchers can create attendance and participation prediction models, they can also quantify trending topics in their respective research community, or they might invent novel recommendation systems helping academics connect to each other with greater ease" (p. 302).

Analysis of Twitter use during academic conferences has been used to describe the social graphs of the related research fields (Borgmann et al. 2016; Desai et al. 2012; Letierce et al. 2010). Letierce et al. (2010) argued that Twitter analysis can identify the hot topics during the conference and provide a posteriori overview of a conference. They further found that Twitter users at a conference make more use of hashtags to ensure their tweets reach the intended audience. Desai et al. (2012) attempted to show how analysis of Twitter use at a nephrology conference can help understand how Twitter is used to disseminate information and to educate the public. They argued that an educational tweet would have (a) informative content (b) internal citations, and (c) positive sentiment. However, they found that informative tweets often were associated with a negative sentiment, potentially due to the formulation of many research findings relating to epidemiology in negative terms. As the authors point out, a limitation of so-called "bag of words" approaches to sentiment analysis is that they cannot capture the compositionality of statements, as negative terms can be used to express overall positive feelings (Socher et al. 2013).

2 Purpose of study

Kimmons and Veletsianos (2016) note that twitter use in conferences differs by discipline. While much work has been done on understanding twitter use as a backchannel in academic conferences from Nursing to Computer Science (e.g., Parra et al. 2016; Salzmann-Erikson 2017), less research has been conducted on education conferences. As such, there is a need to examine how scholars in education use Twitter during academic conferences.

The present study reports on a social network analysis (SNA)—we turn our attention to SNA in the next subsection—of the tweets containing the #AERA2017 hashtag. We attempt to quantify the degree of network centrality, and closeness, of top users, and density of the network. We further provide descriptive statistics to characterize Twitter use during the conference, including a sentiment analysis. Sentiment analysis, also commonly known as opinion mining, is an application of various natural language processing (NLP) techniques to extract, identify, or characterize the sentiment (i.e., opinion or mood) of users in some given situation. Sentiment analysis of twitter data has received growing interest in the literature (Agarwal et al. 2011; Kouloumpis et al. 2011).

3 Social network analysis

Interest in social network analysis (SNA) has exploded in the last few years (Borgatti et al. 2009). SNA has been employed in educational research to quantify the role of social interactions in learning (Grunspan et al. 2014). "One of the most potent ideas in the social sciences" (Borgatti et al. 2009, p. 892), social network analysis is at the forefront of the study of both physical and virtual communities. Borgatti et al. (2009) offered a recent historical review of the field, contrasting network science across the physical and social sciences.

SNA describes social networks in terms of nodes and vertices (edges), where nodes represent actors and vertices represent connections or relationships that can be differentially weighted depending on the degree of connection. Common analytical techniques aim to quantify the degree of network centrality of an actor or group of actors, various calculations address different aspects by attempting to quantify the strength of specific connections within the network.

"A fundamental axiom of social network analysis is the concept that structure matters" (Borgatti et al. 2009, p. 893). SNA can help elucidate the role of network structure in explaining social phenomena. As Padgett and Ansell (1993) demonstrated in their study of the rise of the Medicis in Florence, their high degree betweenness within the network allowed them to broker deals and serve as a political and financial hub. Although there are many studies of network antecedents, the primary focus of network research in the social sciences has been on the consequences of networks. Perhaps the most fundamental axiom in social network research is that a node's position in a network determines in part the opportunities and constraints that it encounters, and in this way plays an important role in a node's outcomes (Borgatti et al. 2009, p. 894).

Educational research studies appear to confirm Borgatti et al. (2009) preceding conjecture; network effects appear very real for learning in social interaction as demonstrated in the three studies reported below (Erlin et al. 2009; Grunspan et al. 2014; Ramanadhan et al. 2009).

Grunspan et al. (2014) offered a primer on using SNA to model classroom network behaviors, finding correlation of degree centrality and betweenness with exam success, finding that greater centrality is related to increased achievement. Similar findings were found by Stepanyan et al. (2010) and Bruun and Brewe (2013). Indeed, a growing body of research has explored outcome-related variables with respect to social networks. As Grunspan et al. (2014) argued, SNA can potentially illuminate the network effects related to more student-centered instructional approaches and help delineate the causal pathways from more active learning methods to increased student success.

Other research has used SNA to analyze student interactions in an online asynchronous discussion forum (Erlin et al. 2009) and in Twitter (Stepanyan et al. 2010). The authors argued that SNA measures like centrality, density, role and network structures can help inform practitioners and ensure that students are not "left behind", that is, excluded from the social graph of the discussion.

SNA can help visualize the network, and help to understand the flow of information through the network (Borgatti et al. 2009; de Laat et al. 2007; Erlin et al. 2009). Abbasi and Altmann (2011) developed a theoretical model of collaboration networks among scholars, finding that scholars with strong ties, (i.e., repeated co-authorships) showed better research performance than scholars with low ties (i.e., multiple single co-authorships).

Ramanadhan et al. (2009) demonstrated how SNA can be used to quantify knowledge transfer in organizations. They reported that the degree of internal and external network connections predicts knowledge transfer and explains over 50% of the variance in skills receipt. Given these strong findings, Ramanadhan et al. (2009) argued that enhancing network connections can be a protective measure to ensure organizational memory and tacit knowledge transfer in organizations with high turnover.

4 Method

Theoretical perspective This study adopts the communities of practice (Wenger 1998) framework and characterizes the AERA conference as representing a constellation of practices operating in tandem and mutually influencing and reinforcing the field of practice of educational research. A community of practice is a group that operates around a common activity and a structured order that develops a local culture and a shared repertoire of practices. They include crafts and professional organizations but also work environments, community organizations, and classrooms. Individuals may belong to different overlapping communities and communities can interact through boundary interactions. A constellation of practices is defined by shared interests and multiple intersecting boundary interactions, whether as transactional knowledge exchange or in mutually reinforcing activities. As there are many varied special interest groups each focused on a specific research area, mutually interacting, the AERA2017 conference represents a constellation of SIG communities organized under an overarching activity, mutually engaging and mutually informing.

Context The context of the study was the AERA 2017 Annual conference held in San Antonio, TX, from Thursday, April 27, to Monday, May 1, 2017.

Sample All tweets containing the #AERA2017 hashtag were downloaded for the two-week period beginning Friday, April 21, and ending, Sunday, May 7, inclusive. The social network analysis was limited to the top 100 users based on number of tweets in the dataset.

5 Statistics

Closeness, degree centrality, betweenness, and density statistics of the social graph of the top 100 users based on number of tweets were calculated using the NetworkX (https://networkx.github.io/) Python package for studying the structure and dynamics of complex networks. These statistics were chosen as they have been shown to relate to performance (Abbasi and Altmann 2011; Stepanyan et al. 2010; Grunspan et al. 2014; Ramanadhan et al. 2009). According to the NetworkX (2016) documentation:

Density The density for undirected graphs is calculated as$d = \frac{2m}{n(n-1)}$ where n is the number of nodes and m is the number of edges in G.

Degree centrality The degree centrality for a node is represented by the fraction of nodes to which it is connected.

Closeness Closeness is the shortest between two nodes. Following Freeman (1979), closeness centrality of a node is defined as the reciprocal of the sum of the shortest path distances from u to all $n - 1$ other nodes. Since the sum of distances depends on the number of nodes in the graph, closeness is normalized by the sum of minimum possible distances $(n - 1)$.

Betweenness Following Brandes (2001, 2008), betweenness centrality of a node v is the sum of the fraction of all-pairs shortest paths that pass through v: $C_B(v)\sum_{s,t\in V}\frac{\sigma(s,t\vee v)}{\sigma(s,t)}$ where V is the set of nodes, $\sigma(s, t)$ is the number of shortest (s, t) paths, and $\sigma(s, t|v)$ is the number of those paths passing through some node v other than s, t. If $s =$ t, $\sigma(s, t) =$ 1, and if $v \in s$, t, $\sigma(s, t \vee v) = 0$.

Sentiment analysis There are various ways to collect and create the training dataset. Some researchers (Pak and Paroubek 2010) have used emoticons such as: -),: D, ☹, etc., while others have used parts-of-speech (n-grams) and hashtags such as #bestfeeling, #success, #epicfail, #worst, etc. (Kouloumpis et al. 2011) and even Partial Tree Kernel (Agarwal et al. 2011), with varying levels of success.

We used TextBlob, a high-level library built-in the NLTK (www.nltk.org) library, to perform sentiment analysis for the current study. Preprocessing of tweets is done automatically, including tokenizing (splitting tweets into individual tokens or terms), removing stop words (commonly used words such as I, an, the, are, is, etc., that are irrelevant to this type of textual analysis) and parts-of-speech tagging of the tokens. The parsed tokens were then fed into a Naïve Bayes classifier to classify whether the tweet's sentiment polarity was positive, negative, or neutral.

6 Results

Three thousand six hundred thirty-five users sent 13,647 tweets during the two-week period with the hashtag #AERA2017, for an average of four tweets per user. In total, 7579 (55.54%) were original tweets, and 6068 (44.46%) were retweets.

Figures 1 and 2 chart the frequency of tweets by day and by hour, respectively. There were a small number of tweets before the conference, the frequency spiked during the conference, and tapered off slowly toward the end of conference.

Table 1 presents the results of the sentiment analysis. We divided the dataset in two groups, including retweets and not including retweets, and conducted a sentiment analysis on both sets. Results showed that about half of all the tweets were positive while less than 10% of the tweets were negative. The rest were neutral for both datasets. Conference organizers could examine negative tweets to confirm whether the tweets are actually negative so that they can act on them to address the concerns posed in the tweets if applicable.

Table 2 lists the top 10 tweets based on the frequency of retweets. It is Twitter etiquette to prefix a retweet with *RT @username:* to send an @mention reply to the original user, letting them know that you gave them a RT (retweet). Some Twitter client apps automatically do this for you when you press retweet button, while others do not. Unless the user retweeting knows the proper etiquette of retweeting and manually adds *RT@username:* before the retweet (if it is missing), it can result in duplicate tweets in the dataset, as can be seen in Table 2. The first tweet, retweeted properly 68 times, was retweeted another 50 times, improperly, that is, without the *RT @username:* prefix. A few more duplicate top retweets can be seen in the table as a result.

Figure 3 shows the top 20 term co-occurrence in the #AERA17 twitter dataset. Frequent terms often provide insights into the most common topics users are engaged with. Individual terms, however, can lose their meaning when taken out of context. Thus, we use two terms that occur together the most in each tweet. This technique preserves the word meaning by recording a part of the context, thereby disambiguating

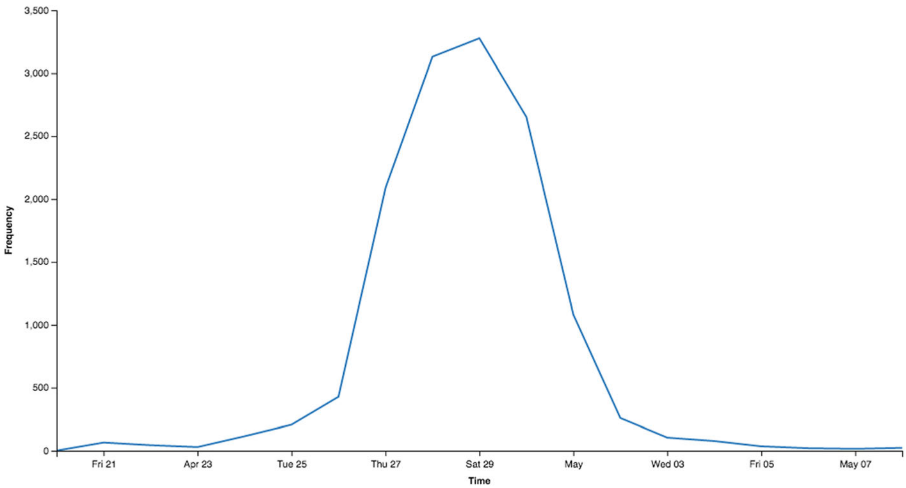

Fig. 1 Frequency of tweets by day

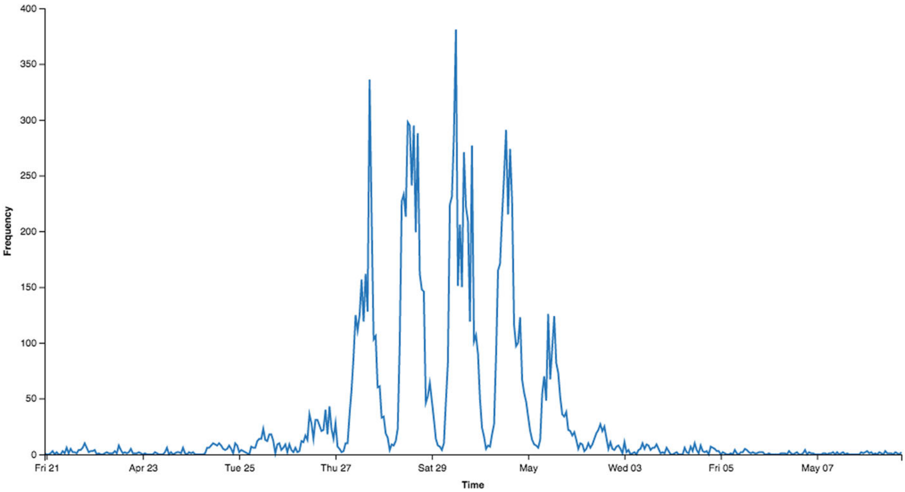

Fig. 2 Frequency of tweets by hour

word meaning and helping to enforce semantic similarity across tweets. For this analysis, we used NLTK's built-in TweetTokenizer API to tokenize each original tweet, ignoring retweets, striping handles (@username), and converting uppercase to lower-case. Further, we removed special characters, stop words, and any term that started with a digit. Each tokenized term was then reduced to its stem by applying the Lancester Stemmer API provided in NLTK. We then built a co-occurrence matrix such that each cell contained the number of times two unique terms appeared in the same tweet. Finally, we selected the top 20 term co-occurrences and plotted the result as a histogram (Fig. 3). Terms antonio + san occurred 249 times together referring to San Antonio city where the conference was held. Forward+look, educ[ation] + research, educ[ation] + teach, learn+teach are other most common co-terms.

Graph density of top 100 users based on number of tweets is 0.17. Table 3 presents the mean centrality statistics for the top 100 users, including maximums, minimums, and standard deviations. Tables 4 and 5 list the centrality statistics for the top 10 users. As can be observed, overall density is low and tapers quickly. However, closeness remains relatively high. Betweenness is relatively low, and tapers off most quickly of all. AERA_EdResearch is the official Twitter account of the AERA and unsurprisingly, it exhibits the highest degree of centrality (0.89), closeness (0.90), and betweenness (0.31). It is considerably higher across all three measures compared to the next

Table 1 Sentiment analysis

	Sentiments with retweets	Sentiments without retweets
Total tweets	13,647	7579
Positive tweets	6265 (45.91%)	3441 (45.40%)
Negative tweets	1085 (7.95%)	642 (8.47%)
Neutral tweet	6297 (46.14%)	3496 (46.13%)

Table 2 Top 10 tweets by number of retweets

Tweet	Retweets
RT @KallieClarkEdu: The educated child has both the knowledge and time to change the world. #education #AERA17 https://t.co/QhrelrW5pH	68
RT @CodyMillerPKY: “Our teachers must be great researchers and our researchers must be great teachers.” -Dr. Gloria Ladson-Billings #AERA17Ã¢Â€Â¦	67
#AERA17 attendees: A roundtable discussion on @AcademicsSay and online academic engagement https://t.co/jdfhbMwt2h https://t.co/AqHDgd55y1	58
RT @AcademicsSay: #AERA17 attendees: A roundtable discussion on @AcademicsSay and online academic engagement https://t.co/jdfhbMwt2h httpsÃ¢Â€Â¦	58
The educated child has both the knowledge and time to change the world. #education #AERA17 https://t.co/QhrelrW5pH	50
Oh @ResearchMark You make my day #AERA17 https://t.co/XHU6QaL9pH	43
RT @KallieClarkEdu: Oh @ResearchMark You make my day. #AERA17 https://t.co/XHU6QaL9pH	43
RT @ResearchMark: Sup #AERA17 https://t.co/Jw0qYH1NJ3	35
Sup #AERA17 https://t.co/Jw0qYH1NJ3	35
“Our teachers must be great researchers and our researchers must be great teachers.” -Dr. Gloria Ladson-BillingsÃ¢Â€Â¦ https://t.co/NIM6JLCHhO	33

highest user, ChrisKBacon (degree of centrality (0.47), closeness (0.66), and betweenness (0.07).

7 Discussion

The overall social network is sparse with low density, with a few very active nodes and many unconnected Twitter users. The degree of centrality and of closeness of the top 10 users is high, relative to the top 100 users. Closeness remains relatively elevated and tapers off slowly, compared to degree of centrality and betweenness that taper off quickly.

These findings are explained by the fact that we employed an undirected graph in our analyses which marks a relationship whether a user follows or is following. As conference attendees are likely to follow the AERA_EdResearch Twitter account,

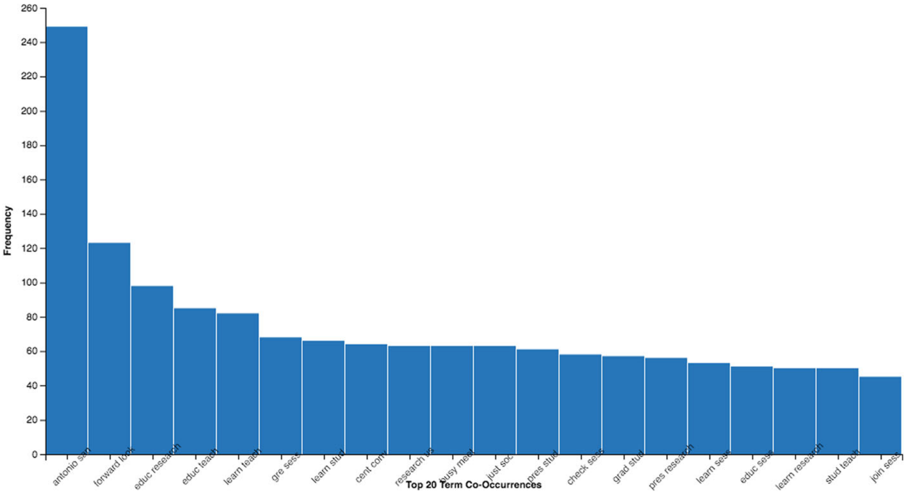

Fig. 3 Top 20 term co-occurrences

many users are connected due to this fact. We interpret this as due to the large number of non-intersecting special interest groups that dilute the overall density and closeness of the network. Within the communities of practice framework, the educational research community can be viewed as a constellation of related but largely non-overlapping practice communities (Wenger 1998). These subgroups can operate virtually independently with little interaction—the overall network exhibiting structural holes (Burt 2004). Thus, Twitter use at the AERA2017 appears to be used as a broadcast medium for communicating across practice boundaries.

Table 3 Network centrality metrics for top 100 users based on number of tweets and top 10 users by degree of centrality

	Degree	Closeness	Betweenness
Mean	0.17	0.53	0.01
Maximum	0.89	0.9	0.31
Minimum	0.01	0.37	0
Standard Deviation	0.13	0.06	0.03
User	Centrality	Closeness	Betweenness
AERA_EdResearch	0.89	0.90	0.31
ChrisKBacon	0.47	0.66	0.07
Education_AIR	0.45	0.64	0.04
brownellcassie	0.44	0.64	0.03
teacherpolicy	0.41	0.63	0.02
jeffpcarpenter	0.40	0.62	0.03
LitProfSuz	0.38	0.61	0.03
wargojon	0.38	0.61	0.02
cherisemcb	0.38	0.62	0.02
ProfessorJVH	0.36	0.61	0.02

Table 4 Top 10 users by degree of closeness

User	Closeness	Centrality	Betweenness
AERA_EdResearch	0.9	0.89	0.31
ChrisKBacon	0.66	0.47	0.07
Education_AIR	0.64	0.45	0.04
brownellcassie	0.64	0.44	0.03
teacherpolicy	0.63	0.41	0.02
jeffpcarpenter	0.62	0.40	0.03
cherisemcb	0.62	0.38	0.02
LitProfSuz	0.61	0.38	0.03
wargojon	0.61	0.38	0.02
ProfessorJVH	0.61	0.36	0.02

Although at the level of the SIG there may be a high degree of centrality, closeness, and betweenness, this is not captured at the level of the whole conference, where the interactions will be largely dominated by the conference organizers and umbrella organizations. Indeed, AERA_EdResearch, as the central node in this network, exhibits a high degree of centrality, and closeness, with respect to the other top 100 Twitter users during the conference, but a relatively low degree of betweenness (0.31) as not all the Twitter users are connected to each other, as they likely belong to different communities of practice but are all related as a constellation of practices, as members of the very broad educational research community.

Limitations This study is limited by its cross-sectional nature. While growth in Twitter usage has been phenomenal, it remains that Twitter is not co-extensive with the conference and analysis of the Twitter network tell us very little about the effective AERA conference network which is much vaster in comparison.

Table 5 Top 10 users by degree of betweenness

User	Betweenness	Centrality	Closeness
AERA_EdResearch	0.31	0.89	0.90
ChrisKBacon	0.07	0.47	0.66
Education_AIR	0.04	0.45	0.64
jeffpcarpenter	0.03	0.40	0.62
LitProfSuz	0.03	0.38	0.61
brownellcassie	0.03	0.44	0.64
ProfessorJVH	0.02	0.36	0.61
teacherpolicy	0.02	0.41	0.63
mtpoc	0.02	0.34	0.60
HarvardCEPR	0.02	0.21	0.56

Future directions Future social network analysis studies of the AERA conference should compare SIGs on various metrics and track their developments over time to gain a picture of the evolving educational research community as it manifests online. Fuller analysis of the social networks of members of the AERA conference, for instance, by including more hashtags relevant to the educational research community during the same time frame, can help inform how the various subgroups evolve and move from the periphery to a more central role. These statistics can help inform conference organizers on central trends in the AERA academic community. They can help organizers react in real-time by modeling conference attendee sentiment or offering different round-tables based on Tweets. Also, perceptions of Twitter use at conferences may provide a complementary avenue of exploration.

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