Social Media Dynamics of Global Co-presence During the 2014 FIFA World Cup

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ABSTRACT

Sports games and other media events can induce very strong feelings of co-presence that can change communication patterns within large communities. Live tweeting reactions to media events provide high-resolution data with time-stamps to understand these behavioral dynamics. We employ a computational focus group method to identify 790,744 international Twitter users, and we track their behavior before and during the 2014 FIFA World Cup. We pick a set of Twitter users who specified the teams that they are supporting, such that we can identify communities of fans of the teams, as well as the entire community of World Cup fans. The structure, dynamics, and content of communication of these communities are analyzed to compare behavior outside and during the event and to examine behavioral responses across languages. Specifically, the temporal patterns of the tweeting volume, topics, retweeting, and mentioning behaviors are analyzed. We find similarities in the responses to media events, characteristic changes in activity patterns, and substantial differences in linguistic features. Our findings have implications for designing more resilient socio-technical systems during crises and developing better models of complex social behavior.

ACM Classification Keywords

H.3.4 Systems and Software: Information networks; H.1.2 User/Machine Systems: Human information pro-

cessing; H.5.3 Group and Organizational Interfaces: Web-based interaction, synchronous interaction

Author Keywords

Twitter; World Cup; collective attention; social TV; second screen; dual screening; social sensor

INTRODUCTION

Social life depends on the presence of others, but the nature of this co-presence can vary across contexts and events. Sporting championships, entertainment spectacles, and other media events can induce very strong feelings of co-presence that can in turn change the structure and dynamics of communication. These changes were traditionally impossible to measure, but social networking services like Twitter have become "social sensors" capturing real-time reactions from large populations of users [42, 44]. Twitter's chronological streams and information sharing practices have made it ideal for supporting interaction around current events [26, 29]. In particular, the practice of "live tweeting" about what users are watching during television broadcasts is contributing to "social TV" experiences with high levels of virtual co-presence [14, 15, 23].

Live tweeting reactions to media events provides high-resolution data with time-stamps to understand behavioral dynamics, relationships to analyze evolving social structure, and content to study changing psychological states. Making sense of these large-scale and complex data requires an interdisciplinary computational social science approach that integrates information retrieval, natural language processing, statistical modeling, and theories from communication, psychology, and sociology [30]. Developing methods and theories to understand collective responses to large-scale events can be used to design more resilient socio-technical systems for supporting collaboration during crises and to develop better models of complex social behavior [45].

In this paper, we use social sensor data from Twitter to analyze how virtual co-presence during media events induce changes in large-scale communication patterns. We

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employ a computational focus group method [33] to identify a population of 790,744 international Twitter users and we track their behavior before, during, and after the 2014 FIFA World Cup. Individual football matches are social occasions for high levels of shared attention and live-tweeting of these events generates very high levels of activity. We examine the structure, dynamics, and content of communication by (*i*) comparing behavior outside of the matches to behavior during the event and (*ii*) analyzing behavioral responses across languages in this international population.

BACKGROUND

The social behaviors and regulations that govern interaction in public life has been a major theoretical concern for sociologists and communication scholars. *Co-presence* is central to many theories and is marked by a feeling of closeness in simultaneously experiencing what others are doing and also knowing that others can perceive what you are doing [18]. Not all occasions are equal in importance and attention. "Media events" are social spectacles that are marked by a collective and mutual awareness that the event is being simultaneously experienced by a large audience, creating a feeling of co-presence that is extremely enthralling compared to events that are less important or of narrower interest [9].

Despite the lack of reciprocity between spectator and performer, mass media consumption can be occasions for sustained and focused social interaction. Television viewers often attempt to actively converse or participate with on-screen actors rather than passively observing the production in a process known as para-social interaction [25]. People enjoy socializing around their consumption of television and other media, even when these media are not the sole focus of attention [11, 14, 34]. Simultaneously watching online videos and participating in online chat can also enhance the experience of watching poor-quality videos and promote stronger relationships among friends and strangers alike [46].

During a media event, Twitter is used as a backchannel where users converge and establish co-presence by using official and emergent hashtags as channels for communal commentary in reaction to a live-broadcast. Participation in this backchannel requires users to use a "second screen" such as a laptop or mobile device to monitor and participate in the social stream of tweets while simultaneously watching the "first screen" of the television broadcasting the event. This "dual screening" allows users to share their own para-social reactions in the backchannel, create and reinforce social relationships with other viewers who are also dual screening, make sense of discrepant incidents through information sharing or humorous improvisation, and potentially see their tweets incorporated into journalists' summaries or the broadcast itself [15, 23].

Users' behavior may switch from conversational orientation towards a known network to self-promoting proclamations towards an imagined audience [5, 35]. Users who were previously reluctant to share popular information for fear of over-saturating their followers may become more likely to retweet it to acknowledge their participation in the event [16]. For example, tweets during the 2012 U.S. presidential debates were marked by sharp decreases in interpersonal communication (replies and mentions) and concentrated attention (replies and retweets) toward elite users [31]. The sentiment of reactions in the Twitter stream also reflects changes in users' support for candidates during political debates [10, 33]. While prior scholarship has examined the extent to which events can be detected and summarized from social media streams [3, 37, 44], there is little research on the changes in social media behavior and structure within the same population over time [31, 33].

RQ1: Do users' activity patterns vary between media events and normal times?

Given the complex demands on attention, users' behavior during media events should differ significantly from non-events. Activity will increase during conditions of shared attention during matches and fall back to baselines after the match concludes.

Shared attention to media events also generates cognitive co-presence characterized by a common ground of mutual expectations and knowledge about what is happening on the broadcast. In typical conversations, participants need to engage in various forms of coordination by presenting and accepting messages to ensure what they have said was understood [8]. However, media events should reduce the need to engage in this coordination by increasing the certainty that the audience for a message shares the same immediate context and experience [38]: not only is everyone watching the broadcast, everyone knows that everyone is watching the broadcast. This cognitive co-presence leads to diminished collaborative effort which should lead to significant changes in linguistic features of speech during media events.

RQ2: How does topical diversity change during an event?

Shared attention should increase common ground as viewers hold common understandings of an event. This will reduce the need for linguistic coordination and also reduce the diversity of topics during the event.

Another important but overlooked dimension of shared attention to media events is the role of linguistic and cultural diversity. The international audience for a media event like the World Cup should reveal global-scale engagement with multi-lingual users, who serve as bridges between otherwise isolated language communities [12, 20, 24, 13]. Activity patterns across languages show very high levels of similarity and geo-located tweets reveal community structure and polarization reflecting historical and cultural boundaries [36]. Linguistic similarity can also reflect underlying cultural affiliations and solidarity as individuals accommodate their partners by employing similar linguistic and topical styles [17, 39, 43].

RQ3: How do users' topics vary with proximity between countries?

Users in geographically proximate countries should exhibit greater topical similarity than users in more distant countries [22]. In the context of a sporting tournament, the fans of eliminated teams should also adopt the topical features employed by fans whose teams are still in competition.

RESEARCH DESIGN

Tweets are nearly-ideal social sensors that involve a large-scale population, provide immediate feedback to events, and allow users 140 characters of unstructured text to express themselves. A common method for analyzing tweet streams is to naïvely aggregate tweets for basic summary statistics or sentiment analysis, which makes assumptions that the population of Twitter users or the processes they use are constant. This is not the case in the context of media events, marked by high levels of shared attention, where the population of users and norms for writing tweets change dramatically [31]. Instead, we adopt a computational focus group model to identify a relevant sub-population and then track its behavior before, during, and after media events [33]. This approach has several benefits as we define a large-scale population sharing a relevant characteristic ahead of time and track only these users' tweets. We identify and differentiate users ("supporters") based on Twitter users declaring their allegiance for a specific team by tweeting a link[1] to a Twitter web page.

Data

The 2014 FIFA World Cup ran from June 12th to July 13th and involved 32 teams playing in a round-robin tournament for the first ("group") stage followed by a single elimination tournament of 16 teams in the second stage. We identified 1,028,756 supporters who tweeted a link indicating their support for a team. Using requests for `user_timelines` from the Twitter REST API,[2] we retrieved up to the 3,200 most recent tweets for each of these users and removed users who posted a link without reference to a team, posted links to multiple teams, or posted fewer than five tweets during the tournament. After this cleanup, our dataset consisted of 790,744 supporters and 129,793,095 tweets.

Table 1 summarizes the distribution of activity among supporters across the 26 national teams that have official Twitter accounts. We computed the average number of tweets these supporters made during the World Cup as well as their average number of followers and friends in August 2014. We observe wide variation in the activity and connectivity of supporters across these national teams. While we use all of the supporters for analysis to see the global trend of supporter behavior during

[1] https://twitter.com/i/t/special_events/world_cup_2014

[2] https://dev.twitter.com/rest/reference/get/statuses/user_timeline

Team	Supporters	Average Tweets	Average Followers	Average Friends
Brazil	197591	133.66	99.53	176.84
Argentina	110639	216.89	121.96	199.70
United States	93781	158.36	132.56	201.88
Germany	82936	192.70	115.75	183.78
Colombia	54347	158.85	98.33	207.85
Mexico	49614	142.27	90.06	182.83
France	25672	206.60	116.12	181.34
Netherlands	24909	248.36	178.33	229.40
Algeria	22415	61.70	33.25	101.65
Spain	16599	137.15	76.33	159.24
Portugal	13965	136.55	80.00	139.49
Italy	13610	135.20	78.73	156.70
Chile	9577	113.59	96.12	178.62
England	8691	114.34	73.80	166.50
Belgium	8379	203.53	97.80	170.51
Australia	7695	68.03	49.61	118.56
Japan	7519	157.67	61.41	168.43
Ecuador	7257	101.61	118.21	167.39
Uruguay	6496	162.50	77.94	179.94
South Korea	5780	124.09	68.56	142.89
Costa Rica	5381	162.47	109.40	208.83
Iran	4394	32.02	83.86	135.42
Greece	4272	103.08	27.24	64.45
Russia	3057	79.96	62.97	79.96
Ghana	2796	144.96	82.13	157.82
Switzerland	2568	83.35	44.13	93.86
Cameroon	804	78.09	27.99	83.92

Table 1. Statistics of Twitter supporters for FIFA 2014 World Cup. These are users who specified which teams they are supporting by using a widely publicized Twitter link. The host team, Brazil, has the largest number of supporters, followed by Argentina, USA, and Germany.

matches and between matches, we choose the four most popular teams, Brazil, USA, Argentina, and Germany, to analyze the behaviors of their supporters in more detail. Out of those four teams, three (Brazil, Argentina, and Germany) reached the final four, whereas the USA team was knocked out of the tournament after the round of sixteen. This provides interesting data, both in the form of repeated observations of events involving the team as well as for measuring shifts in affiliations from supporters of knocked-out teams.
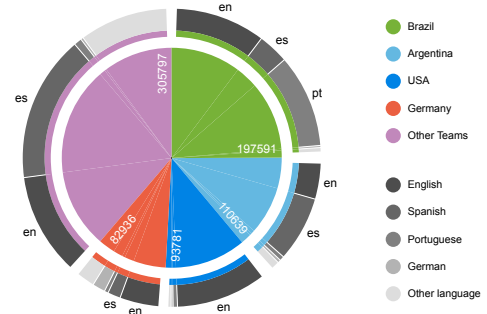

Figure 1. The language distribution of supporters for top four popular teams (and all others aggregated). English is the most used language followed by Spanish.

This international population of users also includes tweets in multiple languages. We labeled the language of users' tweets based on metadata in the `lang` field that

automatically identifies language.[3] In Figure 1, the inner pie chart shows the distribution of top four popular teams and the rest of teams and the outer pie chart is the distribution of supporters' languages for each team. The languages used most, based on the user profile, are English (en), Spanish (es), Portuguese (pt), German (de). There are interesting anomalies such as English and Spanish having the largest language share among the supporters of the German team.

Hashtags, Mentions, and Retweets

Hashtags, mentions and retweets are popular features in Twitter that provide various mechanisms of information sharing among users. Hashtags group messages with similar topics or events, thereby allowing users to band together quickly and easily around a central theme. Mentions allow users to address messages (which are still public) to specific users, thereby allowing directed communication rather than broadcasts of messages. Finally, retweets (RTs) propagate information through user's networks, spreading important messages quickly and widely throughout the twittersphere. Analyzing the patterns of supporters' usage of these features during a global event can reveal important signals about shared attention [31].

With retweets and mentions, we count, normalize, and compare the frequencies before, during, and after each match for each team. We count the number of RTs by each team's supporters on an hourly basis, then normalize the counts by the total amount of tweets by those supporters during each corresponding hour. When we visualize these numbers, we can see definite temporal dynamics. Mentions are analyzed in the same way.

For hashtags, we look beyond the frequency of all hashtags being used before, during, and after the matches. We look at the unique counts of World Cup related hashtags compared to non-World Cup hashtags, and the total counts of those hashtags. We expect to see a high frequency of hashtag usage, especially for World Cup related hashtags, during the match, but we do not expect the unique number of hashtags to change much. To identify the hashtags for World Cup related topics, we note that during this World Cup, Twitter promoted World Cup related hashtags. Specifically, they translated the word "worldcup2014" in multiple languages, and they promoted three letter team codes (e.g., #BRA, #GER), and hashtags of each match by the team codes of the two teams playing (e.g., #BRAvsGER). By analyzing tweets with identical hashtags, we can analyze the adoption of World Cup hashtags among supporters.

Topic Modeling

One key question of shared attention is whether supporters' tweets are focused around a shared set of topics while watching the matches. To answer that question, we analyze the topics of tweets using latent Dirichlet

allocation (LDA), a probabilistic topic model which discovers topics, defined as a probability distribution over the vocabulary, from a corpus of unannotated text in a totally unsupervised fashion [4]. LDA would discover, for example, a topic with the top probability words $\{worldcup, soccer, player, goal\}$. We wish to discover the topics used by the supporters during matches of their teams, during matches of other teams, and during non-match time. Thus, we create three documents for each user, one for tweets from the user during a user's team's matches (MYM for "my matches"), second for tweets from the user during other teams' matches (OTM for "other team matches"), and third for tweets from the user during all other times (NOM for "no match"). We aggregated the users' documents by the teams they support, such that we have a corpus of MYM, OTM, and NOM tweet-documents for each team. We then ran LDA on those corpora using gensim [41]. For LDA hyperparameter settings, we fixed $T = 100$ for the number of topics, $\alpha = 1/T$, and $\beta = 1/T$ as suggested in [19].

RESULTS

Changes in activity patterns

RQ1 asked if users' activity patterns vary between media events and normal times. We hypothesized that during the matches, supporters would show a high level of shared attention, thereby communicating and interacting much more actively compared to other times. Specifically, we measure and analyze the volume of tweets as well as retweets, mentions, and hashtags normalized for the total volume and find evidence of significant changes in communication patterns during events compared to behavior outside of events.

Figure 2 shows the tweeting activity of supporters before and during the World Cup. Supporters show a general increase in tweeting behavior throughout the matches compared to the days before, reflecting the increasing levels of shared attention as fewer teams remain in play. Within each team, supporters show a definite pattern of intense tweeting during the matches as each team shows a distinctive pattern of peaking at different times. For example, Germany and Argentina, which played in the final round for the title, both peak during that final match. Brazil peaks during the semi-final match between Brazil and Germany. USA peaks at the round of 16 (at which point they are out of the tournament) but they maintain a steady amount of activity until the end.

Figure 3 plots the normalized activity levels for the populations of supporters of Germany, USA, Argentina, and Brazil. Across all four examples, we find similar evidence of retweets making up the largest share of tweets, followed by tweets containing mentions, and finally tweets containing hashtags. Comparing different behaviors during and outside game times, we find that mentions fall while retweets rise during games. This replicates prior findings that interpersonal communication declines while rebroadcasting increases during these events [31]. We
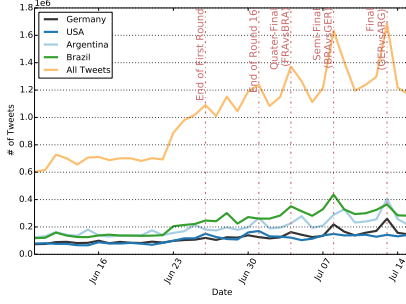
Figure 2. The total number of tweets for all supporters (orange) and Brazil (green), Argentina (light blue), Germany (black), and USA (blue). Brazil peaks at the semi-final match (Germany vs Brazil), and Germany and Argentina peak at the final match. USA peaks at the round of 16, after which it is out of the tournament.

Figure 3. Day-by-day volumes of retweets, mentions and hashtags, normalized by the number of tweets that day, for Brazil, Argentina, USA, and Germany. In general, retweets and hashtags peak on the days of important matches, whereas mentions do not.
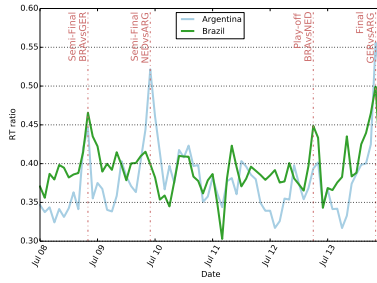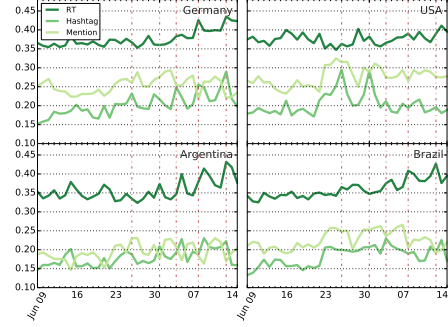

Figure 4. Hourly retweeting volume, normalized by the total number of tweets, for Brazil (green) and Argentina (light blue). These peak during the time of important matches; shared attention leads to more propagation of existing messages than new message creation.
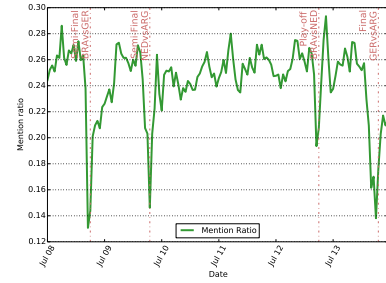

Figure 5. Hourly mention volume, normalized by the total number of tweets. Mentions show a reverse pattern of decreasing during moments of shared attention. This is consistent with previous work explaining that mentions occur relatively infrequently during shared attention.

also observe significant variation in the rate of hashtag usage, a topic we explore more in the next section.

Figure 4 shows the dynamics of retweeting for Brazil supporters (green) and Argentina (blue), normalized by the total number of tweets from these supporters. Retweets peak during important events as users prioritize spreading and responding to the existing messages rather than generating new messages. Because "dual screening" is cognitively demanding, this suggests users are temporarily adopting alternative behaviors to communicate with their networks as well as signal their membership in the event. After the event ends, the retweeting rate returns to normal levels reinforcing the hypothesis that these anomalous behaviors are driven by the exigencies of shared attention to media events. Although Argentina and Brazil never played each other in the tournament, they exhibit strong coupling of activity patterns. These archrivals both have spikes when the other team is playing, which suggests that supporters of Argentina are closely following and responding to the Brazil games and *vice versa*. This reflects a generalized kind of media event induced co-presence in which affinity as well as (presumably) animosity induces significant changes in communication behaviors across large populations of users.

Figure 5 shows the dynamics of hourly total mentions during World Cup, normalized by the total number of tweets. The mention ratio significantly drops during important matches. This suggests that directive communications are not happening during shared attention. After the event ends, the mention rate returns to its normal levels, which suggests such dynamics are driven by the exigencies of shared attention to media events. To validate the significance of retweet, mention and hashtag frequency between match days and non-match days, we computed two-sided t-tests for top 4 most popular teams, Brazil, Germany, Argentina and USA, between each team's match days and non-match days. The p-values for these tests were all lower than 0.001.

Changes in topical diversity

RQ2 asked how topical diversity changes during an event. The large number of people attending to an event might introduce more hashtags into the ecosystem as supporters improvise humorous titles or try to find backchannels with less noise. However, we hypothesized that shared attention should decrease the needs for linguistic coordination and thus reduce the diversity of topics while the event is happening. As we discuss below, we find evidence for both increasing number of hashtags as well as decreasing entropy in conversations.

Team	MYM	OTM	NOM
Brazil	2.05 (-)	2.16 (+5.42%)	2.19 (+6.81%)
USA	2.09 (-)	2.46 (+17.55%)	2.84 (+35.59%)
Argentina	1.94 (-)	2.09 (+7.52%)	2.24 (+15.19%)
Germany	2.04 (-)	2.25 (+10.45%)	2.52 (+23.40%)
All Teams	2.35 (-)	2.42 (+4.40%)	2.61 (+14.29%)

Table 2. Average topic entropy values for supporters matches (MYM), other matches (OTM), and no match (NOM). For all teams, there is lower entropy during own matches when tweets center around World Cup topics.

Event	Example tweets
MYM (USA vs Ghana)	Its time for this nation to show the world what are we capable of Lets go USA I wanna see Miroslav klose :c @xxxxx best game ever :)
OTM (Brazil vs Mexico)	@xxxxx: Enjoy it cause the next two games we will probably lose Que golazo ! @xxxxx wiwi they can beat Portugal tho
NOM	Im so good at cutting hair made the best hairstyles lol haha and it was my first time lol ! @xxxxx okay now its time to watch some videos goodnight !

Table 3. Example Tweets for supporters matches (MYM), other matches (OTM), and no match (NOM).

Figure 6 plots the changing number of all hashtags, which fluctuates during games and steadily grows until the end of World Cup. World Cup matches, as shared experiences, drive drastic increase of hashtag generation (blue line), which are driven primarily by changes in hashtags frequency related to World Cup (green line). The number of official World Cup hashtags also follows similar trends during the same period of time. Each peak happens at important matches, such as semi-final and final matches. However, the number of unique hashtags stays steady throughout World Cup in the figure. These results show that users demonstrate a limited adoption of hashtag variety, but the frequency of hashtags increases as shared attention to a media event intensifies.

To quantify shared attentions during World Cup matches using hashtags, we computed entropy values (p-values less than 0.001) for the hashtags used each day from June 10 to July 15. Lower entropy values manifest as sparser distributions and indicate tweets were concentrated in fewer hashtags while higher entropy values represent denser distributions reflecting tweets using many more hashtags. In contrast to the emergence of more hashtags during the matches from Figure 6 above, Figure 7 shows that the entropy of hashtag use falls dramatically during matches. This indicates that the event unifies attention of Twitter users and triggers users to tweet using the same hashtags. We also observe a negative trend towards the final match, indicating a general loss of diversity in hashtag use over the course of the entire World Cup. We interpret this as users concentrating their attention more intensely on fewer teams.

We computed analogous entropy measures (p-values less than 0.001) for the distribution of topics for each supporter's tweets during matches when their team was playing (MYM), when another team was playing (OTM), and when there was no match being played (NOM). We provide examples of these tweets in Table 3. Table 2

BRAZIL SUPPORTERS TOPICS		
	Label	Top words
en	Match (o)	match time world win good team
	Players (o)	madrid messi cup cristiano
	App (x)	free google playing app ios apple
	General (x)	love people know good life
pt	Score (o)	cup brazil match goal team germany
	Players (o)	brazil david copa luiz neymar
	Media (x)	twisting bestfandom playlist added
	General (x)	day life want love happy person
GERMANY SUPPORTERS TOPICS		
	Label	Top words
en	Final (o)	ger germany arg brasil bra final
	World Cup (o)	world cup win match
	General (x)	one people love best
	General (x)	india one good time modi world
de	Final (o)	ger germany arg brasil bra final
	Champion (o)	germany worldchampion thanks
	Gaza (x)	gaza israel gazaunderattack palestine
	Media (x)	mtvhottest one tomorrow today
ARGENTINA SUPPORTERS TOPICS		
	Label	Top words
en	World Cup (o)	world cup win match team match
	Soccer (o)	footyjokes factfootballl messi
	Day (x)	love day happy one best
	General (x)	people someone one life
es	Players (o)	messi daddies best gigliotti
	Final (o)	arg thanks messi argentinaalafinal
	Greeting (x)	hello world give welcometoargentina
	Day (x)	life today want always
USA SUPPORTERS TOPICS		
	Label	Top words
en	World Cup (o)	soccer cup world brazil messi germany
	Team (o)	game team win play
	General (x)	love get people one know
	Twitter (x)	follow please love much thanks

Table 4. Four high probability topics obtained during supporter's own matches (o) and no match (x) from Brazil, Germany, Argentina, and USA supporters in its top two languages. Words in Portuguese, German and Spanish are translated into English via Google Translate.

summarizes these differences in average entropy values across all users among all teams as well as breaking out results for each of the top four teams we discussed above. Using the MYM as a baseline, we see that topical diversity for users during others' matches (OTM) increases by 4.4% on average while topical diversity increases by 14.29% outside of match time. Such findings indicate that media event-induced co-presence can trigger significant changes in communication content.

We identified two topics that show high probability for MYM and lower probabilities for OTM and NOM. Similarly, we identified two topics that show high probability for NOM and lower probabilities for MYM and OTM, both for the top two languages for each team. We show the topics by the high-probability top words in each topic in Table 4. We translated the top words in Portuguese (pt), German (de), Spanish (es) into English using Google Translate. We labeled the topics manually to discuss and refer to them easily.
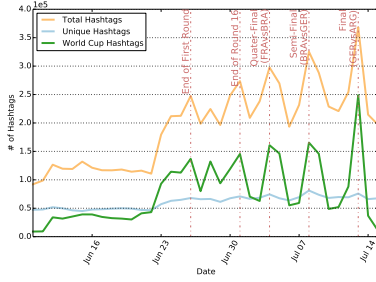
Figure 6. Number of unique hashtags, total occurrences of hashtags, and occurrences of World Cup hashtags. The number of unique hashtags stays flat, but the number of the occurrences of hashtags has high peaks during important matches, signaling shared attention.
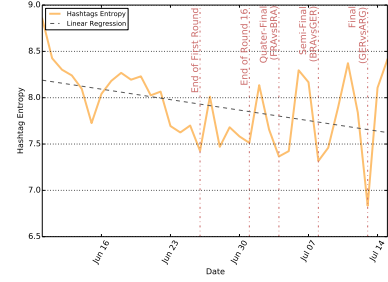

Figure 7. Hashtag entropy during World Cup. There is a trend of decreasing entropy, shown by the orange regression line, showing more frequent uses of the popular hashtags. Troughs during important matches are highly pronounced, as soccer fans use the World Cup hashtags.

English-speaking Brazil supporters tweeted about topics *Match* and *Players*, topics closely related to the World Cup. Similar to English-speaking Brazil supporters, Portuguese-speaking Brazil supporters tweeted about World Cup topics, *Score* and *Players*, during the matches. When there is no match, supporters tweeted about *Media* and *General* topics. The difference between English-speaking and Portuguese-speaking Brazil supporters is that Portuguese-speaking supporters tweeted about Brazilian soccer players, whereas English-speaking supporters posted non-Brazilian soccer players during Brazil matches. Both German-speaking and English-speaking Germany supporters had *Final* topics related to their Final match against Argentina. One interesting topic found in NOM for German-speaking Germany supporters is Israel-Gaza conflict(*Gaza*) topic, which happened on July 8, 2014. Finally, USA supporters also show World Cup related topics for MYM, however, top words lists do not contain their team but other team or player names. Early elimination of US team may have resulted in fewer tweets about topics related to the team.

Geographical and topical proximity

RQ3 asked if users' topics vary with proximity between countries. We expected that supporters from geographically proximate countries should exhibit greater topical similarity than supporters from more distant countries owing to linguistic accommodation and style matching.

We ran LDA using all tweets from every team's supporters during the championship match of Argentina versus Germany. The output of LDA are "topics" which are probability distributions over the vocabulary, often visualized as the list of top probability words, as shown in Table 4. Another output, which is referred to as θ [4] and is computed for each document in the corpus, is the vector of probabilities for each topic. That is, for each of k topics found by LDA, the value of the kth dimension of θ_d represents the proportion of topic k within document d. For our data, we aggregate all of the tweets from each supporter during the Argentina vs Germany match into a single document, so θ_d is the vector of topic proportions for the tweets written by that supporter during that

particular match. We ran LDA on the set of such documents for all supporters of all teams, then we averaged the *theta*s for all supporters of each team. Then we computed the similarity between each of these teams' average topic proportions and the Argentinean supporters' average topic proportions using Pearson's correlation, which ranges from -1 (no correlation) to +1 (high correlation). Table 8 plots these topical similarities. Figure 8 plots these topical similarities as a function of the normalized geographic distance between the centroids of each country i: $-\sqrt{|(x_{ARG} - x_i) + (y_{ARG} - y_i)|}$. We observe a very strong fit between geographic distance and topical similarity during this final and highest shared attention event; neighboring countries like Uruguay and Chile exhibit the highest similarity while distant countries like South Korea and Japan have very low similarity.

We replicate these results using Germany as a comparison in Figure 9. We find a weaker but similar pattern in which neighboring countries like Belgium and the Netherlands have some of the strongest similarities while distant countries like Colombia and Uruguay have lower levels of similarity. However, there are some outlier countries that violate this pattern such as Australia, which is distant but similar, and France, which is close but dissimilar. These suggest other factors may play a stronger role in some cultural contexts than distance alone.

DISCUSSION

The 2014 FIFA World Cup was a media event that generated intense levels of shared attention. This attention manifested itself in fans' communication patterns as they used Twitter to generate high levels of social co-presence. We identified a population of 790,744 Twitter users who explicitly expressed an allegiance for a team and clustered their behavior together to compare across teams and games. Unlike prior work that has examined large-scale behavior changes during shared attention to media events in the context of national political events [31], this study collected data about people with diverse linguistic and cultural backgrounds responding to the same event of international importance. Using a "computational focus group" data collection strategy [33], we were able to collect public data about large-scale behavioral change
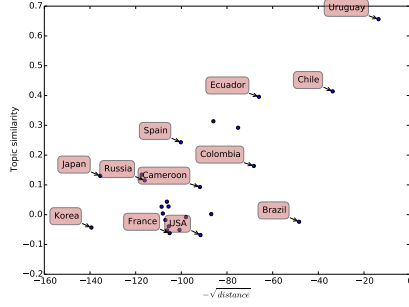
Figure 8. Topic similarities between Argentina and other supporters during the final match (Germany vs Argentina) as a function of geographic distance between the countries. Other South American supporters are closer to Argentina supporters in their topics except Brazil.
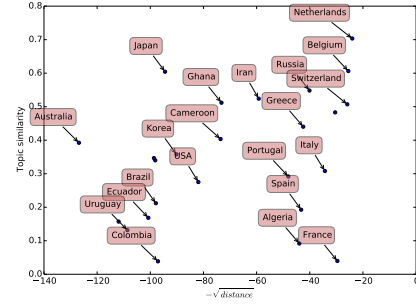

Figure 9. Topic similarities between Germany and other supporters during the final match as a function of geographic distance between the countries. European supporters are closer to Germany supporters in their topics. We can also see that Japan is close in topic similarity.

while preserving our ability to conduct within-subjects analyses. Specifically, we were able to compare the same users' behavior before, during, and after media events rather than trying to generalize from posts matching a single hashtag. This permitted us to extend prior findings about media event-induced co-presence as well as to understand how their behavior and content changes in response to heightened levels of co-presence.

For RQ1, we observed significant increases in the volume of tweets made during the matches as supporters "dual screen" to tweet about what they were watching during the matches. During matches, the rate of re-tweets increased while the rate of mentions decreased. Similarly, the number of hashtags generated during the matches increased significantly but with low rates of adoption by users. Large populations simultaneously attending to multiple media sources may impose high levels of cognitive overhead, which leads to the adoption of different collective behaviors. In effect, users perform different roles or assume new identities during media events compared to their "everyday" identities outside of media events. Users de-emphasize interpersonal communication like mentions because they potentially want to reach a broader audience during the event or it is difficult to enter this information quickly enough to be relevant.

RQ2 asked how topical diversity changes during these events. We found the overall entropy of hashtags used in the aggregate conversation during matches actually fell significantly below the baseline outside of the matches. While hashtags are an imperfect measure of linguistic diversity, they are examples of temporary linguistic communities reflecting a form of coordination among users to speak to larger audiences [7, 32]. The reduction in diversity we observed during games points to a profound desire to interact synchronously with a global audience despite the presence of language barriers or absence of their own team.

RQ3 asked how fans' topics varied with the proximity between the countries. We found that the makeup of topics that supporters discussed varied depending on whether their team was playing, and the similarity of supporters'

topics in the championship match was correlated with the distance between the countries. The role of social identification with the team as well as the geographic proximity to the focal team's country broadens our understanding of how a multi-lingual and multi-cultural online community understands and responds to shared topics of interest [12, 13, 20].

Implications
Despite popular perceptions that new technologies have made television less social as it moves from the "public" family room to more "private" mobile devices, our findings contribute to the tradition of "interaction television" within HCI scholarship as well as related concepts like "social TV" [21, 14]. The use of Twitter during media events like the World Cup has implications for (1) developing new theories around temporary and synchronous social behavior within socio-technical systems, (2) designing technology to support implicit social interactions under mediated co-presence, and (3) understanding cross-cultural and multilingual interaction.

Prevailing scholarship about online communities emphasizes the importance of encouraging contributions, promoting commitment, regulating behavior, and socializing newcomers [28], but this research often proceeds from assumptions that motivations to participate in online communities are constant over time. However, the media event-induced co-presence we observed around the World Cup adds to related scholarship around crisis informatics that explores how communities can temporarily coalesce in response to exogenous factors [40]. Lessons from these emergent and temporary communities can inform the design of online communities generally to promote greater resiliency under stress as well as responsiveness to boundary conditions like the "bursty" dynamics we observed. Moreover, the ubiquity of these "bursty" dynamics throughout human social behavior [1] invites additional theoretical and empirical scholarship to understand how these episodes support the adoption and diffusion of technologies and practices throughout the community, socialize new members into substantive roles, and structure users' online and offline social lives.

Seen through a theoretical lens, our findings suggest users share temporary normative expectations to not impinge on their friends' attention to the game by sending notifications that might distract them. Implicit interactions are pervasive in social life as we accommodate our behavior and interactions to varying contexts and demands for attention and levels of initiative [27]. However, many systems are notoriously bad at managing implicit interactions as machines demand our attention through notifications that occur without the explicit request of a user. Although further research is needed, users' varied uses of retweets and mentions during these events may reflect meta-cognitive attempts to avoid behaviors that generate notifications for their friends (texts and mentions) that, in turn, create obligations breaking their friends' attention to events both are enjoying. During highly synchronous and co-present media events, users may potentially employ implicit interactions by adopting behaviors and shifting communication to less disruptive channels like retweets and favorites that do not create obligations to reply. Systems could be designed that incorporate individuals' or large-scale populations' social media streams as sensors for the availability and "distractability" of users for system notifications.

Finally, our results around global co-presence can inform research and design for multi-lingual interaction. While the World Cup is a unique event, which potentially limits the generalizability of our findings to more common media events, these media events are also ideal empirical settings for measuring cross-cultural behavior. The inherent noisiness of Twitter data for measuring context and sentiment within — much less across — languages is widely acknowledged [2, 6], but media events allow researchers to measure the within-subject responses of a large global population to the same stimulus. The potential for corpora like this to aid in benchmarking new methods for multilingual content analysis, as well as comparing communication behaviors across cultures and geographies, is immense. These corpora likewise reveal different cultural constructions of the same events as well as the role of multilingual users in bridging geographic and cultural divides within online communities [20, 22].

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