Uncovering Social Media Reaction Pattern to Protest Events: A Spatiotemporal Dynamics Perspective of Ferguson Unrest

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Abstract. Social platforms like Twitter play an important role for people to participate in social events. Utilizing big social media data to uncover peoples reaction to social protests can shed lights on understanding the event progress and the attitudes of normal people. In this study, we aim to explore the use of Twitter during protests using Ferguson unrest as an example from multiple perspectives of space, time and content. We conduct an in-depth analysis to unpack the social media response and event dynamics from a spatiotemporal perspective and to evaluate the social media reaction through the integration of space, time and tweet content. We propose to answer the following research questions. (1) What is the general spatiotemporal tweeting patterns across the US? (2) What is the spatiotemporal tweeting patterns in local St. Louis? (3) What are the reaction patterns in different US urban areas in space, time and content?

1 Introduction

Social movements such as protests have significant impacts on public policies and political decisions. Understanding the social movements is important because engaging in this kind of collective efforts is one of the limited methods for ordinary people to pursue their political goals [10]. In recent decades, the development of new information and communication technologies have led to increasing political participation through information spread, opinion expression and activism [9,11,16]. Specifically, social media platforms can provide the public with easier access to protest plan details and affect peoples motivation to participate, thus facilitating protests both locally and globally [13]. Compared to traditional media, they can deliver protest information at a high speed, allow active participation in event organization, search information as needed, and bring pre-vetted information through personal social networks [13,16]. Hence social media can provide users enriched experiences involving themselves actively in the events rather than simply receiving news. For example, during the Arab Spring, digital media, especially Twitter, has prompted the protest mobilization through reporting real-time event magnitudes and providing basis for collaboration and emotional mobilization [2,11].

In recent years, Twitter has rapidly become one of the most important media for information dissemination and communication. Users can use Twitter to identify interesting topics, express opinions and share news with the public: traditional media can use Twitter to quickly transmit the latest news, while normal users can exchange viewpoints with friends or strangers. Due to the large amount of users conveying their thoughts on Twitter, the great quantity of newly released tweets can lead to information burst at an astonishing rate through the social media network in response to social issues. People can thus generate concrete understanding of movement process in multiple dimensions by analyzing large amount of related tweets and exploring spatiotemporal patterns through Twitter. Especially for researchers, tweets are important crowd sourced data to learn the reaction patterns and real thoughts in social movements. In this way, we can fully understand the ongoing trends and objective opinions of protests in time through the detailed tweet information including time, location and content.

On August 9th, 2014, an unarmed black teenager, Michael Brown, was shot to death by a white police officer, Darren Wilson, in Ferguson, a suburban area of St. Louis, Missouri. This incident quickly spread on Twitter, Facebook and other platforms. Meanwhile tensions between the public and police in Ferguson boiled over which led to riots. Several nights of protests were held to support transparent investigation while state of emergency and curfews were implemented there. More and more related reports were posted on Twitter. Hashtags like #Ferguson and #TheyGunnedMeDown became popular. The tweet count spiked right after the shooting, indicating the growing attention among people from local to global. Protesters also utilized Twitter to organize events by spreading plans, sending announcements and collecting donations [7].

Though many studies use social media data to study social movements, most of them examine the large-scale pattern in social networks or focus on the content in small-scale data. In this study, we are motivated by the lack of efforts in comprehensively understanding the social media usage and reaction pattern towards protests integrating space, time and content. Our main contributions are: (1) a detailed analysis to unpack the social media response and event dynamics from a spatiotemporal perspective; (2) an in-depth study of the social media reactions through the integration of space, time and content. We aim to answer the following questions using the Ferguson unrest as an instance. (1) What is the general spatiotemporal tweeting patterns across the US? (2) What is the spatiotemporal tweeting patterns in local St. Louis? (3) What are the reaction patterns in different US urban areas in space, time and content?

2 Related Work

Existing research has examined how social media influenced the information spread and user reactions in social movements. Gaby and Carens study showed that social media platforms like Facebook helped spread social movement information quickly and reach large amount of audiences [8]. During the 2011 Tunisian

and Egyptian Revolutions, Twitter has supported conversations among different types of users including normal people, activists, bloggers and journalists by examining news dissemination and user activities [12]. In addition to information dissemination, social media have played an important role in increasing normal peoples participation in social protest events. Poell and Borra [14] assessed user participation in social media protest reporting based on a set of tweets, videos and photos related to the Toronto G20 protest event from Twitter, YouTube and Flickr. They found that YouTube and Flickr did not facilitate users participation in reporting while Twitter to some extent has more alternative reporting. Valenzuelas study of protests in Chile also suggested that frequent use of social media for opinion expression has significantly positive relationship with protest participation [17]. Tufekci and Wilson [16] further pointed out that social media use could greatly increase the odds for respondents to attend protests on the first day, while traditional media did the opposite. In addition, Earl et al. [6] identified that Twitter created a new dynamic in the protester and police interaction as it has been frequently used by protesters to share information about protest details and the actions of police.

Furthermore, previous studies have integrated spatial analysis methods to explore the social movements by analyzing the social and information network structures. Conover et al. [4] tried to understand if the spatial patterns of communication networks could reflect the goals and needs of protest movement Occupy Wall Street. They reached the conclusion that the network had high levels of locality while non-local attention mainly focused on high-profile locations. Croitoru et al. [5] examined the spatial footprint, social network structure and content of both Occupy Wall Street and Boston Bombing Twitter datasets in both physical and cyber spaces to understand the information exchange during social movement events. Bastos et al. [1] investigated the relationship between the locations of protesters attending demonstrations and those of the users who tweeted the protests during the 2013 Vinegar protests in Brazil. Their study indicated that users tweeting the protests were geographically distant from the street protests and that users from isolated areas relied on Twitter hashtags to remotely engage in the demonstrations.

As ordinary users commonly have different activity patterns compared to media outlet accounts [18], our work differs from earlier studies by emphasizing on the spatiotemporal reaction patterns of ordinary people to the protest events. We start with analyzing the general tweeting patterns towards the Ferguson protest event. Next we explore the reaction patterns in space, time and content. Further we compare the different reactions among different urban areas.

3 Dataset

From August 10th, 2014 to August 27th, 2014, we collected 13,238,863 tweets mentioning Ferguson using the Twitter Streaming API. In total, 2,052,364 unique users are included in this dataset. Among all the 13 million tweets, 72.87% of them are retweeting tweets while 3.47% are in reply to others, indicating that

retweeting is the major behavior in information diffusion. Around 0.833% of all tweets are tagged with geographical coordinates. In addition, we obtained multiscale geographical data of US from 2014 TIGER/Lines Shapefiles to assist our analysis.

4 Data Preprocessing

As we are interested in the spatiotemporal behaviors of ordinary Twitter users, we focus on the geo-tagged tweets to study the users behaviors from social type and initiative perspectives. First we compare the time series trend and behavior patterns of geo-tagged and non-tagged tweets. Then we distinguish the media outlet accounts and eliminate out their tweets to avoid potential bias in analyzing local peoples reactions.

4.1 Measurement of Reaction Types

Existing studies have utilized different measurements to evaluate users' influence and activity considering following and retweeting relationships [3, 19]. Here we evaluate the reaction patterns of Twitter users from social type and initiative perspectives.

Social type can be identified by ones social network built on Twitter. It can be a result of users' response to certain events on Twitter, or an indication of activity, authority or influence in real life so that they tend to react more in Twitter. We categorize users into different social types based on the numbers of their followers and friends, which represent their past activities. Based on the two features, we use K-means clustering method to classify the users to three levels: influencer, intermediary and acceptor. Within each level, users have similar overall prestige. The users with followers far more than friends act as the influencers in the social type, the users with friends far more than followers act as the acceptors, while users who have similar numbers of followers and friends play the part of medium.

Initiative specifically reflects users preferences of posting original tweets. To observe whether users tend to post new tweets or retweet to spread information, we evaluate the initiative by calculating each users retweeting ratio with the number of retweets divided by the number of all tweets one posted. Based on the ratio distribution, we group the users to three classes with different initiative levels. If the ratio is less than 0.2, the user mainly publishes new tweets and contributes new content to Twitter. Then we label the user as high initiative. Users with retweeting ratio higher than 0.8 are categorized as low initiative with passive action because they mainly retweet from others. Then the rest of the users are considered to have medium initiative. In general, 21.4% of all users mainly publish new tweets with retweets ratio of almost 0, while 58.4% mainly retweet.

4.2 Geo-tagged and Non-tagged Tweets

After defining the reaction types, we clean our dataset prior to any data analysis. We first remove the tweets related to other topics such as Alex Ferguson or Connie Ferguson and the retweeted tweets posted before August 10th. According to Morstatter et al.s study [13], geo-tagged tweets collected from Streaming API can evenly represent all tweets locations in North America. Thus using geo-tagged tweets to represent the spatial distribution of all tweets is plausible. In addition, we check the distribution of daily tweet count for both geo-tagged tweets and all tweets and computed their correlation to ensure that the temporal patterns are consistent in general (Fig. 1). The Pearsons r correlation of the daily tweet count reaches 0.9985, indicating that the frequency distribution of the two datasets are highly linearly correlated. Hence using geo-tagged tweets for analysis will not introduce bias to the temporal data distribution.

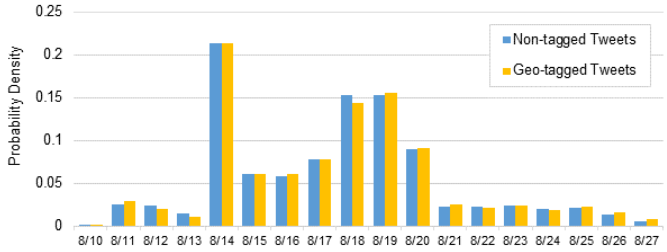

Fig. 1. Histogram of non-tagged tweets and geo-tagged tweets in US by dates

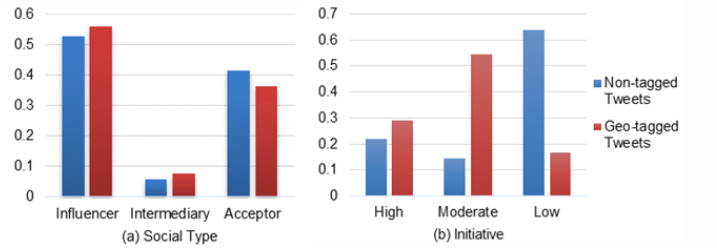

Fig. 2. Percentage of different social type and initiative levels for users who post geo-tagged and non-tagged tweets

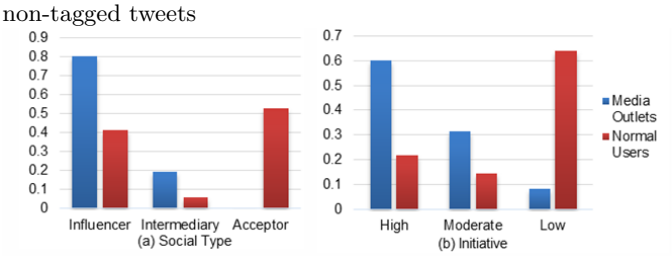

Fig. 3. Percentage of different social type and initiative levels for media outlets and normal users

We further compare the reaction of users who add geo-tags and who do not. The result shows no significant difference among users of all social types (Fig. 2(a)). The percentage of influencers among the users who post geo-tagged tweets is relatively higher than that among those who do not, though the difference is not obvious. This suggests that tweeting with or without geo-location is not influenced by ones social network structure. For different initiative levels (Fig. 2(b)), however, the result shows that users who tweet with geo-tags have significantly higher initiative of publishing more new tweets compared to those who do not. The user group with geo-tagged tweets has a larger proportion of people with high and moderate initiative compared to the group with non-tagged tweets, indicating users who tweet with geo-tags tend to have higher initiative to post original tweets.

4.3 Media Outlets and Normal Users

Playing a more influential and active role in investigating and disseminating news, media outlet accounts usually act differently from normal social media users [18]. With large number of followers, tweets posted by these accounts always spread quickly and have broader audiences. Thus including them in our spatiotemporal analysis may lead to bias in understanding normal users reactions. Here we apply the Support Vector Machine (SVM) classification method incorporated with manual processing to distinguish media outlet accounts and further examine if media outlets have different reaction patterns when compared to ordinary users.

To characterize media accounts, we extract nine features regarding users social network, influence and tweeting behaviors including: number of followers, number of friends, status count, number of tweets, number of retweets, number of replies, average retweeted times and average replied times during this event. For classification training, we randomly sample 200 accounts and label 30 of them as media outlets with instances of TV news (e.g. CBSEveningNews), newspapers (e.g. Washingtonpost) and self-media accounts (e.g. JMitchellNews). We use SVM to train our model, and then manually review accounts labeled with media to identify real media account next. With modified labels, next we retrain the model and repeat the above process. Finally we identify 108 media outlet accounts out of all users.

With classified media outlets and normal users, we further evaluate the two groups' reaction patterns. From Fig. 3, we find out that about 80% of media outlets act as influencers with large amount of people listening to them. None of the media outlets is an acceptor, meaning that they mainly play a role of publishing and disseminating information. About 60% media outlets have high or middle initiative, indicating that they actively publish new tweets in general. However, there are still a minor proportion of media outlets that prefer to retweet rather than publish new tweets. On the contrary, normal users in this event are more passive to publish original tweets as around 63.89% of them have low initiative. Regarding the social types, more than half of normal users act as acceptors. Still, there are almost 40% of normal users act as influencers in this

event. The comparison of media outlets and normal users shows that media accounts in Twitter still work as traditional media with high initiative and strong influence. Even though many normal users participate in the Ferguson event and post new tweets on Twitter, their influence is not comparable to the media outlets. Most normal users still act as channels to spread information created by others.

In summary, geo-tagged tweets can represent the spatial and temporal distribution of the whole tweet dataset, while the users who post geo-tagged tweets tend to have higher initiative than those who do not. In addition, media accounts turn out to have quite different reaction behaviors, which could lead to bias when analyzing spatiotemporal behaviors of normal users. As a result, we eliminate tweets by media users out for our further study.

5 Research Questions

In this paper, we focus on analyzing the spatiotemporal dynamics of the Ferguson event in detail from different spatial scales by addressing answers to three research questions. Research question 5.1 examines the general spatiotemporal patterns across the whole US. Research question 5.2 digs into the spatiotemporal tweeting patterns and specific events happened in local St. Louis. While research question 5.3 further compares the reaction patterns among four major US urban areas in space, time and content.

5.1 What is the General Spatiotemporal Tweeting Patterns across the US?

Spatial Distribution. To examine the general tweeting patterns in US, we apply the Average Nearest Neighbor (ANN) and Kernel Density Estimation (KDE) methods to evaluate the general spatial distribution of tweets in US. ANN compares the average distance between each feature and all nearest neighbors to that of a hypothetical random distribution. Then it determines whether the point features is clustered, dispersed, or randomly distributed in space. Different from ANN, KDE is a density-based method to calculate the feature density in a neighborhood around each of these features. In detail, it estimates a density at each feature location by counting the feature number in a small region defined by kernel value centered at the feature location. The ANN result shows that the significance level p-value is smaller than 0.05, suggesting that geo-tagged tweets are highly clustered in US. The Kernel Density map (Fig. 4) shows that there are obvious high density of tweets in St. Louis near the incident in the Missouri and Illinois boarder. Other high density areas can be easily identified in main urban areas like New York and Washington DC, while the tweet density in other areas is generally low.

After examining the general spatial tweeting pattern, we utilize a Density-Based Spatial Clustering of Applications with Noise (DBSCAN) method to accurately identify the most highly clustered tweeting areas. DBSCAN groups

closely packed points with plenty of nearest neighbors together and makes them as outlier points compared to low-density regions. In DBSCAN, we set the minimum sample size in a neighborhood to 5000 and identify four largest clusters in St. Louis, New York, Washington DC and Los Angeles urban areas (Table 1). Among all the four urban areas, St. Louis has the highest tweet count, though the other three areas are large urban areas with higher population than St. Louis. Thus we can infer that local St. Louis people have more intense reaction to the event. By integrating all above methods together, we can generate a thorough understanding of the spatial tweeting pattern in this case.

Table 1. Number of tweets in four urban areas

Location	St. Louis	Washington DC	Los Angeles	New York
Number of tweets	12,434	4,657	4,329	7,628

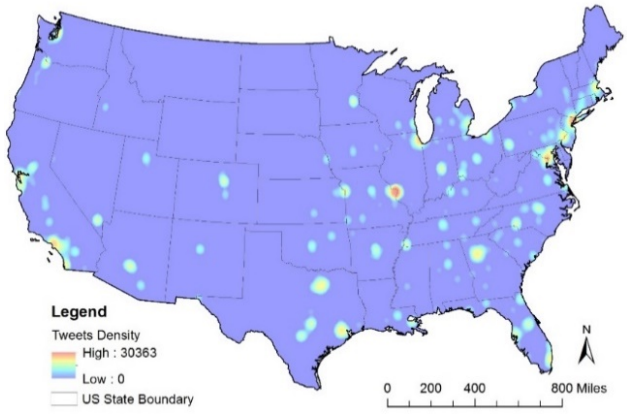

Fig. 4. Kernel density map of tweet counts in the US

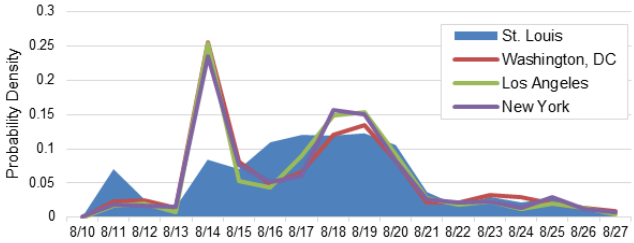

Fig. 5. Histogram of daily tweet counts in the four urban areas

Temporal Trend. To understand the usage trend in time, we examine the daily tweet counts from August 10th to August 27th, 2014. Similarity of temporal pattern among New York, Washington D.C. and Los Angeles can be found easily, while St. Louis shows a completely different trend (Fig. 5). St. Louis tend to have

relatively even response during the whole period, while other three areas have a peak on August 14th and then some more response during August 18th to 19th. Specifically in St. Louis, the first peak emerges on August 11th right after the event happened. Then the count keeps increasing from 12th till 18th, during which time Governor Nixon declared emergency state in Ferguson and imposed a curfew. However for the other areas, the highest peak exists on August 14th, when President Obama addressed the nation on the situation in Ferguson, saying there was no excuse for protesters to turn to violence or for excessive force by police. During 17th and 18th, another peak occurs in other areas related to the Governors declaration and curfew. Then the percentage for all places became low after the 21st.

To quantitatively compare the temporal trend, we calculate Root-mean-square Deviation (RMSE) and Pearsons r correlation of the daily tweets distribution densities from the four areas to those of the whole geo-tagged tweet dataset. In addition, we compute the skewness to measurement the asymmetry of daily tweets probability distribution. The results (Table 2) suggest that New York, Washington DC and Los Angeles are more positively skewed compared to St. Louis. The RMSE value of St. Louis is around 0.04 while the values of the other cities are only around 0.01. The correlation between St. Louis and the whole geo-tagged tweets is only 0.77 while the correlations between the other cities and the whole geo-tagged tweets are over 0.99. These indicators suggest that St. Louis tweets have obviously different temporal pattern compared to other places in US in general.

In summary, tweets are highly clustered in US, especially in large urban areas such as St. Louis and New York. In particular, local St. Louis has the most concentrated tweets. Also, the temporal trend of St. Louis is different compared to other areas in US.

Table 2. Skewness, RMSE and correlation results for four urban areas

Urban Area	Skewness	RMSE	Correlation
St. Louis	0.22787	0.03706	0.77001
New York	0.55577	0.00947	0.99019
Washington D.C.	0.57499	0.01451	0.97174
Los Angeles	0.50537	0.01145	0.99185

5.2 What is the Spatiotemporal Tweeting Patterns in Local St. Louis?

For this question, our purpose is to focus on the local St. Louis area and identify where, when and what are local people tweeting about during the protest.

Spatiotemporal Hotspots To explore the small-scale pattern within St. Louis, we apply a spatiotemporal clustering method Space-Time Permutation Scan

statistic to identify significant tweeting hotspots in St. Louis. Originally designed for detecting disease outbreaks, this method uses only time and location data to identify potential spatiotemporal clusters. It makes minimal assumptions about the time and location, and adjusts for natural purely spatial and purely temporal variation.

Fig. 6 shows the four identified clusters in St. Louis. The western part of St. Louis has a cluster covering a large area with 1453 tweets from August 11th to 14th, corresponding to citizens first reaction peak to this event. Then in the Ferguson area near the incident, there are two smaller tweeting clusters during August 15th to 17th and August 20th to 21th. These two clusters match well in space and time with the local protests happened on West Florissant Avenue and the burned Quiktrip store in Ferguson. Then at the end of our data collection period, there is another small tweeting cluster from August 25th to 26th located close to the Friendly Temple Missionary Baptist Church, at which the funeral of Michael Brown held on August 25th.

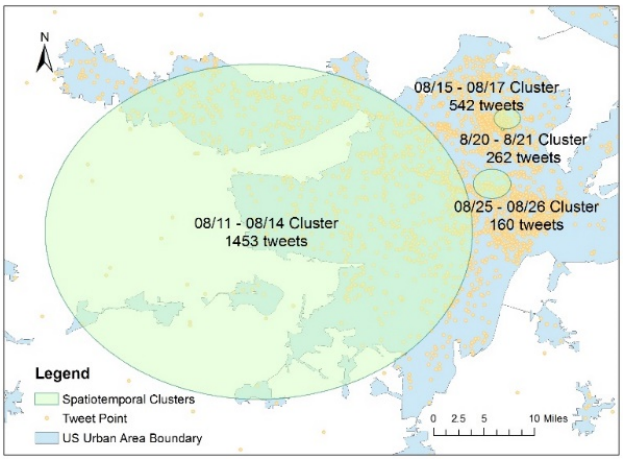

Fig. 6. Spatiotemporal clusters identified in St. Louis urban area

Text Analysis. In addition, we dig into the tweet content to examine how people responded to the hot issues in this event on Twitter. As the general sentence length in our tweet dataset is not suitable for commonly used topical modeling algorithms, in this study we calculate and compare the frequencies of popular terms tweeted in our dataset.

We start with the tweets extracted from the four clusters in St. Louis to identify the topics that people are mostly interested in. First we calculate the frequency of each term considering its different forms. For example, Peaceful is regarded the same as Peace. "Governor" and "Nixon" all refer to the Governor Nixon of Missouri. We then remove the most tweeted terms that appear commonly in all clusters, such as Ferguson, Michael Brown, Police, etc. For the cluster from 25th to 26th, during which time Michael Browns funeral was held,

the word funeral has a high occurrence frequency. While almost nobody talks about it in tweets from other clusters. In the cluster from 15th to 17th, Quiktrip is among the highest frequency words. This is corresponding to the fact that the Quiktrip store at which the shot happened, was the epicenter of the protest and was looted and burned by the angry protesters during the unrest in those days. Similarly, during 20th to 21st, the Florissant has high frequency, in accordance with the protests held on the West Florissant Avenue at that time.

Thus by extracting the local tweeting clusters and identifying the tweet content, it is easy to find out that the local spatiotemporal tweeting patterns strongly reflected the real-time events happened in local St. Louis area.

5.3 What are the Reaction Patterns in Different US Urban Areas in Space, Time and Content?

After exploring the spatiotemporal tweeting patterns in two different spatial scales, we further study the reaction patterns of ordinary Twitter users in space, time and content by comparing the four representative urban areas including St. Louis, Washington DC, New York and Los Angeles.

Twitter User Reaction in Space. To analyze whether geography plays a role in user reaction we mainly looked at the data from two perspectives: 1) Users in and out of St. Louis. 2) Users in four cities: St. Louis, Washington DC, New York and Los Angeles.

We first separate users into two groups: in and out of St. Louis. By comparison of the users' reaction types (Fig. 7), we find out that for both groups, more than 50% the users who respond to the Ferguson event are influencers. The percentage of influencers is relatively higher outside St. Louis. Around 30% of them also act as acceptors to receive information from others. While more users in St. Louis play the role of intermediary to spread news and opinions. We further conduct an independent-samples t-test to examine the difference of social types in and out of St. Louis. With p-value equals to 2.2e-16. The result suggests that the users social types are significantly different in and outside St. Louis. We also look into the percentage of people who have high, moderate or low initiative in Ferguson event. Regarding initiative, users in St. Louis tend to publish original tweets more while users out of St. Louis retweeted tweets more. Comparison of social types shows that tweets published by users in St. Louis are retweeted more than other tweets. The possible reason is that users in St. Louis report the events with twitter, then the news is spread to other places.

For the second analysis, we focus on comparing the reaction patterns of users in the four different urban areas. Result (Fig. 8) shows that in St. Louis more ordinary users are active, because active users with fewer followers are more than other areas. Meanwhile, the Twitter users in St. Louis tend to have a larger percentage of high and medium initiative than those in the other three cities. There is not much difference in user types among Washington DC, New York and Los Angeles. We further compare the being retweeted times for tweets

in the four cities and find out that tweets posted in St. Louis are retweeted 8.55 times on average, which is several times higher than that of the three other cities, which are separately 4.17, 3.84 and 1.97. This result also suggests that tweets generated by users in St. Louis have higher influence and are more valued than those generated in other areas.

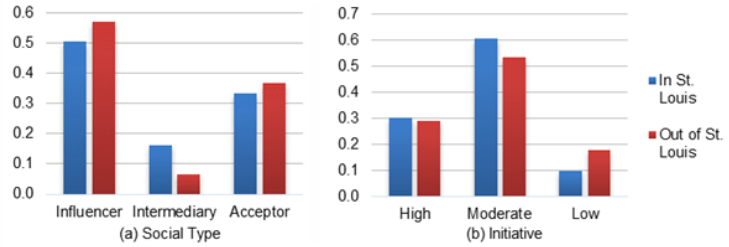

Fig. 7. Percentage of different social types and initiative levels for users in and out of St. Louis

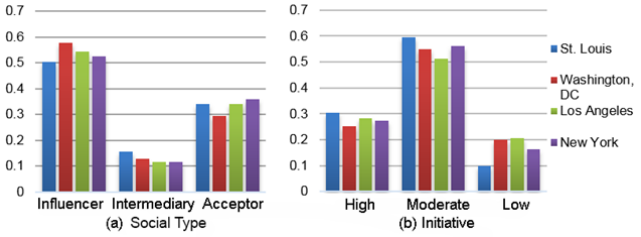

Fig. 8. Percentage of different social types and initiative levels for users in the four urban areas

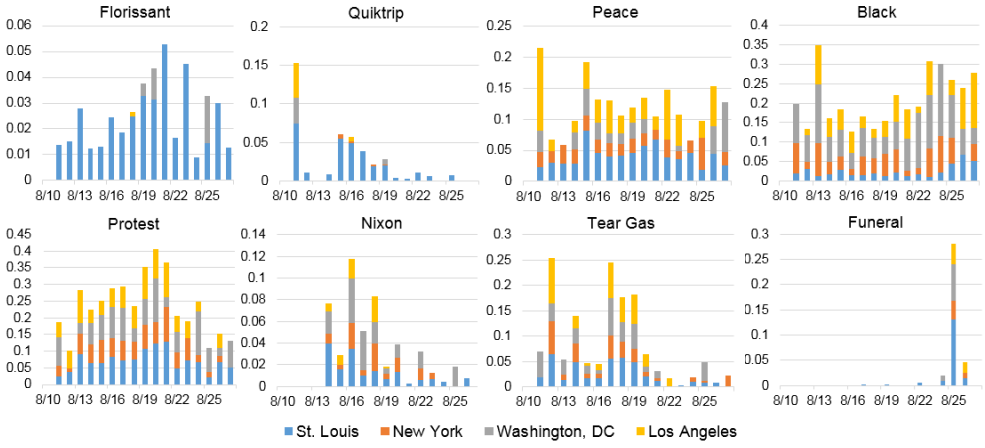

Fig. 9. Popularity trends of the selected eight terms in the four urban areas

Text Analysis. Based on the text analysis session in 5.2, we identify eight terms with different context to further compare their daily popularity trends in different areas: Florissant, Quiktrip, Peace, Black, Protest, Nixon, Tear Gas and Funeral. "Florissant" and "Quiktrip" are corresponding to the local protest events happened in St. Louis. Peace, Black,and Protest stand for the common topics that people will talk about regarding social movements related to racial problems. While "Nixon", "Tear Gas" and "Funeral" are more about the news commonly reported about the protest status. For each term, we compute the rate of term frequency to the total tweet number during each day for all the four cities. We then use the Analysis of Variance (ANOVA) test to quantitatively measure the difference of the trends. Specifically, we conduct two groups of ANOVA test: (1) all four cities; (2) the three cities other than St. Louis.

Table 3. ANOVA test results for the selected eight terms

Words	p-value (4 cities)	p-value (3 cities)
Florissant	2.26e-15*	0.088669
Quiktrip	0.000774*	0.676055
Peace	0.024167*	0.105103
Black	3.75e-05*	0.008304*
Protest	0.24671	0.402924
Nixon	0.273281	0.203327
Tear Gas	0.828834	0.748623
Funeral	0.742757	0.884234

From Fig. 9, it is easy to find that words representing local event, such as Florissant and Quiktrip, were mainly discussed in local St. Louis area. ANOVA result (Table 3) shows that for both words, there are significant differences among all four cities while no difference among the cities outside St. Louis. This indicates that local people care more about the local event and may use Twitter to exchange details for the protest plans, such as the tweets Marching up and down W Florissant and Group of men in purple robes and shirts marching north on Florissant Ave in #Ferguson anyone know what organization they're with? Even though we exclude big media outlets, smaller media accounts may also get into St. Louis to report the latest progress on Twitter, such as Protests are peaceful right now on west Florissant. We'll bring you an update from Ferguson tonight on 41ActionNews. For the words about popular social movement topics, our results suggest that local people talk more about "Peace" or "Justice", while words related to race such as "Black" is more popular outside St. Louis and have various popularity trends among different cities. Moreover, for the words about the general public events and announcements made by politicians such as "Tear Gas" and "Nixon", they tend to have similar popularity patterns among users in different areas.

Combining the previous analysis in space, time and content, we can identify that Twitter users in different areas have different reactions towards the protest events. People in St. Louis show higher initiative for attending the online discus-

sion and are more active in spreading and accepting the information about the protests. Local people tend to respond to and publish tweets about the issues related to event details, while people from other areas have response to the general topics related to the events. Besides, announcements from politicians such as the President and Governor can attract public attention in large spatial coverage, which can be reflected on social media platforms like Twitter.

6 Conclusion

In our study, we have conducted an in-depth analysis to understand the social media response and protest event dynamics from a spatiotemporal perspective using Ferguson unrest as an example. Also, we have explored normal people's reactions through the integration of space, time and tweet content. Specifically, we have focused on measuring how people react on Twitter from the social type and initiative aspects.

Our results have shown that media outlets have much higher influence and initiative compared to normal users. Normal users who post geo-tagged tweets tend to have higher influence and initiative than those who do not, though the difference of influence is not obvious. In general, tweets in US are highly clustered in urban areas, especially St. Louis and large cities like New York, Washington D.C. and Los Angeles. The daily temporal patterns vary between St. Louis and other urban areas. The spatiotemporal clustering analysis indicates that tweets inside St. Louis have significant spatiotemporal clusters, suggesting the existence of hot issues in local area in correspondence to the real protest events happened in St. Louis. Though users in St. Louis have less followers, they tend to publish more original tweets and have higher retweeted times than users in other areas, suggesting that their words have higher popularity on Twitter. In addition, text analysis indicates that people in various areas have different responses to different terms. More local people tend to respond to local event details, while people from other areas have responses to the general topics related to the events. Besides, politicians announcements to the public have broad audiences during the protests. Future work will focus on the network structure, sentiment analysis and socioeconomic factors in detail to fully understand the mechanisms of information spread and user interaction in social protests.

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