Examining Twitter Mentions Between Police Agencies and Public Users through the Lens of Stakeholder Theory

Yun Huang
School of Information Studies,
Syracuse University
Syracuse, USA
yhuang@syr.edu

Qunfang Wu
School of Information Studies,
Syracuse University
Syracuse, USA
qwu114@syr.edu

Youyang Hou
School of Information, University of Michigan
Ann Arbor, USA
youyangh@umich.edu

ABSTRACT

Police agencies increasingly leverage social media for community policing. This paper examines how municipal police agencies and public users interact on social media by examining their mentioning behaviors on Twitter. We manually annotated 7,142 tweets sent by 14 municipal police agencies within 6 months in 2015, and classified 15,785 tweets where public users mentioned the agencies. Through the lens of Stakeholder Theory, we also classified 10,956 Twitter users, who either mentioned the agencies or were mentioned by the agencies, into different stakeholder groups. Using both qualitative and quantitative methods, we identified patterns of how they mentioned each other. For example, agencies mentioned more popular and local stakeholders, while less popular and non-local stakeholders sent more negative tweets. We discuss implications of the results for police agencies, which include how to better identify and engage stakeholders and foster community policing on Twitter.

CCS CONCEPTS

•**Human-centered computing** →*Social media;*

KEYWORDS

Community Policing; Stakeholder Theory; Twitter Mentions.

ACM Reference format:
Yun Huang, Qunfang Wu, and Youyang Hou. 2017. Examining Twitter Mentions Between Police Agencies and Public Users through the Lens of Stakeholder Theory. In *Proceedings of dg.o '17, Staten Island, NY, USA, June 07-09, 2017,* 9 pages.
DOI: http://dx.doi.org/10.1145/3085228.3085316

1 INTRODUCTION

According to a survey by the International Association of Chiefs of Police (IACP), approximately 96.4% of 553 U.S. law enforcement agencies use social media [1]. Social media platforms, which allow people to share information instantly and facilitate mutual interactions, are found to enable police agencies to handle crimes more effectively, and to promote a reciprocal relationship between the police and community members [11], as well as to increase perceived police legitimacy [14]. Thus, an increasing number of municipal police departments are using social media to support the development of community policing [2], where the agencies try to build partnerships and solve problems with all members of the community [9].

However, the use of social media is still new to police agencies [8, 16]. Police agencies use social media mainly to keep the public informed but also for investigation purposes [3, 26]. Agencies either had a narrow view of social media's potential value or lacked a long-term vision [8], and they were ill-equipped to make use of the intelligence of the networks [39]. Also, community policing had been understood as being bound to a certain physical geographic location [34]. Agencies face new challenges of managing police-stakeholder relationships within ever-growing social networks as social media allows all kinds of users to interact with police agencies directly, including those outside of the local communities [8, 10]. On Twitter, the mention feature (using "@" and a particular user name in the tweet) is an effective way for users to interact with each other [36]. However, little is known regarding how police agencies and public users mention each other on Twitter.

In this paper, we use Twitter mentions to examine the interactions between police and public users through the lens of stakeholder theory. This model originally addressed how organizations could manage and satisfy the interests of various stakeholders [13]. Its model of stakeholder salience, focusing on stakeholders' power, legitimacy, and urgency [13], has been used to explain the dynamics in online activities, e.g., eGovernment [12, 32] and eParticipation [4, 30]. We focus on 1) how police agencies mention stakeholders with different levels of salience; and 2) how different stakeholders mention police agencies.

We collected 7,142 Twitter tweets sent by 14 municipal police agencies and 15,785 public tweets where agencies were mentioned within 6 months in 2015. We also collected the user profiles of 10,956 users who were either mentioned in these tweets or who were senders of the tweets. Through both qualitative and quantitative analyses, our work made the following contributions: 1) three code schemes: one for classifying user roles to identify different stakeholders involved in the interactions, and two for classifying agency tweeting strategies and public tweets' topics respectively, to understand when interactions between agencies and different stakeholders happen; 2) new findings of interactions between police agencies and public stakeholders with different levels of salience using Twitter mentions; 3) discussions on the potential of using the three code schemes and Twitter mentions to engage stakeholders more effectively on Twitter for community policing.

dg.o '17, Staten Island, NY, USA

DOI: http://dx.doi.org/10.1145/3085228.3085316

2 RELATED WORK

In this section, we review the relevant literature on community policing, social media, and stakeholder theory, then we propose our research questions.

2.1 Police Agencies' Social Media Use

Research studies have examined how law enforcement agencies use social media as an effective channel to disseminate information such as crime, traffic, and safety notifications to a large audiences in a timely manner [10, 11]. However, agencies' use of social media has been limited primarily to informing the public, and less so for collaborative interaction with citizens [6] to either send alerts, or to receive suggestions regarding day-to-day policing [29].

Social media has great potential to support community policing, which refers to the partnership between residents and police that is developed to address neighborhood-specific issues; in this partnership, residents are involved in decision-making processes and engage in local problem solving [34]. Scholars emphasize the importance of collaboration between police officers, residents, and organized stakeholders in combating crime and decreasing resident fear [31]. There is a great need to understand how police agencies leverage social media to engage with various stakeholders in community policing.

A framework consisting of three strategies that government agencies frequently used on social media, including *Push*, *Pull*, and *Networking*, has been proposed [22, 24]. *Push* is a one-way strategy with the goal of providing transparency. More specifically, when the *Push* strategy is applied, social media sites are used as an additional communication channel to get the message out. *Pull* is a two-way strategy with the goal of engaging the public by soliciting information or requesting certain actions. *Networking* is a strategy with the goal of cross-boundary two-way communication, leading to collaboration between the government agencies and the public. Prior research found that agencies sent more *Push* messages than *Pull* messages on their websites [28] and on Facebook [16]. In this work, we investigate agencies' use of different social media strategies on Twitter for community policing.

RQ1: How did police agencies use *Push*, *Pull* and *Networking* strategies on Twitter?

Social media platforms allow organizations to engage stakeholders in different types of interactions, such as comment, reply, mentions and media [33, 40]. For instance, Bonson et al. [5] analyzed what types of media, content and behaviors generated more user engagement on Facebook, and examined stakeholders' reactions (i.e., likes, comments and shares) and mood (i.e., positive or negative comments). Recent studies on nonprofit organizations showed that nonprofits engaged with stakeholders on social media through different interactions [21]. Among all these social media features, mentions were found valuable for understanding organizational engagement with stakeholders. For instance, Hou and Lampe [15] found non-profit organizations leveraged mentions to engage different stakeholders (e.g., volunteers and funders) by showing recognition, asking questions and building relationships. However, little is known about how police agencies interact with different stakeholders using mentions.

RQ2: When did police agencies mention stakeholders on Twitter?

2.2 Stakeholder Theory and Stakeholder Salience

Stakeholder theory has its roots in management during the 1980s as an effective tool for organization and public sectors to identify which stakeholders need more of their attention [13]. Through the identification and evaluation of stakeholders and stakeholders' relationships, organizations can better manage the public environment, relationships, responsibilities and interactions in their strategies and implementation [4, 30].

One important component of the stakeholder theory framework is stakeholder salience, which is defined as "the degree to which managers give priority to competing stakeholder claims" [25]. In particular, stakeholder salience is evaluated using three criteria: power (being able to bring about the outcomes desired), legitimacy (a perception or assumption that the actions of the stakeholders are desirable and appropriate within socially constructed systems of norms, beliefs, and definitions), and urgency (the degree to which stakeholder claims call for immediate attention) [25]. Salience analysis can be used to identify and classify different stakeholders[12]. Researchers demonstrated that conducting salience analyses provided a deeper understanding regarding why stakeholders participated in online activities in various contexts, e.g., eGovernment [12, 32] and eParticipation [4, 30].

On social media, the stakeholder's power is related to the centrality of their position in the online community; legitimacy is related to the relevance of the content discussed and shared; and urgency is related to the intensity and frequency of discussions on particular issues [33]. For instance, Johannessen et al. counted different user roles' salience on social media [17]. In their study, politicians have high power, legitimacy and urgency, while local media and municipal administration have only high legitimacy but low power and urgency. In our study, we analyze stakeholder salience in the police agencies' stakeholder network on Twitter.

RQ3: Which stakeholders (in terms of different levels of salience) did the agencies mention more on Twitter?

On the other hand, stakeholders with different levels of salience may have different communication preferences or behaviors on social media. Previous research found that stakeholders with high salience were less likely to participate in social media but stakeholders with lower salience were the opposite [17]. Stakeholders with higher salience tend to use more traditional channels for communication [17]. However, social media platforms provide low cost, direct, controllable communication channels for stakeholders with lower salience to shift the power of communication from public relations practitioners to social media users [35]. For example, activists can become more powerful or salient to an organization when their network density, closeness centrality, and degree centrality increase in the organization's stakeholder network. We are interested in examining who mentioned the agencies on Twitter, what they mentioned, and if there were any patterns in their mentions.

RQ4: How did stakeholders with different levels of salience mention police agencies on Twitter?

3 METHOD

In this section, we present how we collected, prepared and annotated the data for the following data analysis.

3.1 Tweet Data Collection and Cleaning

Data for this study was collected using Facepager [18], a tool for collecting tweets. We configured the collection using the Twitter REST API in order to understand what the agencies sent on Twitter, and how many interactions (e.g., favorites and retweets) the tweets received. We analyzed the Twitter accounts of police agencies located in cities that either ranked in the top 50 most populated cities of the U.S., or ranked in the top 10 for high crime rates. These accounts are of interest because the volume of safety-related events or topics that the police agencies tweet about in their community will probably be more than those in smaller cities or cities with low crime rates. Not all agencies had official Twitter accounts. Through this method, we narrowed our search to 52 accounts. We further randomly selected 14 police accounts and collected a total of 7,142 tweets sent by these 14 agencies between February 17 and August 13, 2015.

Meanwhile, we ran Twitter's streaming API to collect public tweets that mentioned any of the 14 agencies within the same period of time. Because we were interested in how public users tweeted about the agencies, we cleaned up the data by only selecting the tweets that were firstly created by public users. Eventually, within the study period, we collected a total of 15,785 tweets where public users mentioned the agencies.

3.2 Annotation of the Tweets

3.2.1 Code Scheme of Agency Tweets. In order to understand the agencies' tweets, we manually annotated all of the 7,142 agency tweets. We developed a two-tier code scheme by analyzing the purpose and the topic of each agency tweet. Drawing from the aforementioned literature [22, 24], we used three social media strategies, i.e., *Push*, *Pull* and *Networking*, as the first level of the code to describe the general purpose of a tweet. In brief, *Push* strategy serves as a communication channel to help spread the message; *Pull* strategy asks the public to interact with the agencies or other people by sending requests in the tweets; and *Networking* strategy encourages an informal way of interactive communication between the agencies and their respective community by sending non-mission critical information. Within each category, we further developed a second level of the code, which was used to help understand specific topics of the tweets. The final coding scheme contains 8 topics. We provide sample tweets in Table 1.

- *Push*: Within the *Push* category, *Crime* defines tweets that convey information about a crime incident. The crime incident can be related to shootings, homicides, arrests, victims, guns, drugs, etc. *Traffic* defines tweets that relate to road conditions, such as real-time traffic, road construction alerts, and expected traffic delay alerts. *Announcement* defines tweets that communicate non-crime and non-traffic information.
- *Networking*: Within the *Networking* category, *Tip* defines tweets that communicate suggestions to improve public safety and to avoid potential danger. *Personnel* defines tweets that address individual names of police department employees. *Appreciation* defines tweets that express gratitude and appreciation. *Information* includes all other non-tip, non-personnel, and non-appreciation tweets. Unlike the *Announcement* of the *Push* category about public-safety alerts, the *Information* topic in the *Networking* category is used to reach out to the public to build long-term trust and relationships, e.g., informing the public about an upcoming better-family-life workshop, in order to engage more participants for local collaboration.
- *Pull*: The *Pull* tweets are about requests for various pieces of information (e.g., missing persons or criminals wanted). Since there were very few *Pull* tweets in total, we combined them into one topic, *Request*, which is defined as tweets that ask the public to provide information about critical issues, such as identifying a crime incident or finding a missing person.

Strategy	Topic	Agency Tweet
Push	Announcement	3 alarm fire burning on Lorain Avenue (not related to protests) hoping our #firefighters stay safe @Cleveland_FFs
	Crime	Arrest made & this gun was taken off the streets of #Maspeth #Queens by cops from the @NYPD104Pct #800577TIPS http://t.co/XlfGDeT7Ef
	Traffic	Area of 112/ Airport Way clear, will be reopened to traffic. @PPBPIO will brief media at designated location in 10
Networking	Appreciation	Thanks to instagram user @madirink for posting this photo during the ELCA Conference this weekend in #Detroit! http://t.co/qFIAKIS1hC
	Information	Joint SPD and CHP Explorer training tonight at CQB City. @CHP_HQ http://t.co/5ow17RnsUb
	Personnel	Officers Laskey and Goodrich "protecting" the @VoodooDoughnut float. #CopEatingADonut #NationalDonutDay http://t.co/MJUdf01Gso
	Tip	Check out this great app from the @FBI for tips and crucial info if a child goes missing http://t.co/TrJMW5qLJR http://t.co/7vWwxz0XGQ
Pull	Request	WANTED: M/H and F/H for hate crime and slashing throat of M/24 on 3/12 at Seneca and Gates Ave @NYPD104Pct Call #800577TIPS http://t.co/Kq87Itkv9I

Table 1: The Code Scheme and Samples of Agency Tweets

We hired 3 coders and trained them to understand the coding rules and concepts. Then two coders started to independently code the remaining tweets. Each of them first annotated tweets into the first coding level independently. Without any discussion, two coders then independently annotated tweets into the second code level based on their first coding level results. We computed the Cohen's Kappa to evaluate the inter-coder agreement [38]. The results showed almost perfect agreement (0.81 $\sim$ 0.99) for each category and substantial agreement (0.61 $\sim$ 0.80) for each topic.

3.2.2 Code Scheme of Public Tweets. Given the large amount of public mention tweets, we randomly selected 1,706 of them and annotated them first, then used the annotated data to classify the other 14,079 public mention tweets.

We went through a procedure similar to the way in which we annotated the agencies' tweets. When developing the code book, we consulted with previous annotation schemes in varying contexts [7, 27]. For example, public tweets in crisis situations [27] were classified into four categories: 1) Information-related; 2) Emotion-related; 3) Opinion-related and 4) Action-related. However, we found that using these four categories to annotate our data resulted in a low inter-coder agreement, because it was very difficult to distinguish negative Emotion-related tweets from negative Opinion-related tweets. Similarly, it was not easy to distinguish positive Emotion-related tweets from positive Opinion-related tweets in our data set. Thus, we decided to merge the Opinion-related and Emotion-related categories into an Expression-related category. Finally, we created three categories for the first level code and six topics for the second level code. Sample public tweets are provided in Table 2.

- Expression-related: For negative tweets, we further split them into *Negative* (e.g., sarcastic or criticizing) and *Strong Negative* (e.g., taking a stance against the agencies), because some tweets were condemning the agencies, which was regarded differently from tweets that criticized the low quality of agency services. There were many tweets expressing appreciation or other emotional support; we coded them to *Positive*.
- Information-related: For some tweets delivering or collecting information, we split them into *Sharing* and *Seeking* respectively.
- Action-related: The Action-related tweets are kept using one code *General*, indicating that the category covers all kinds of action-related tweets; this differs from the above *Seeking* topic which regards actively looking specifically for information rather than calling for other types of action.

The Cohen's Kappa value of each code showed almost perfect agreement (0.81 ∼ 0.99) , expect that *General* had substantial agreement (0.61 ∼ 0.80) [38]. We used the annotated tweets as the foundation to classify the rest of the public mention tweets using the SVM algorithm in Scikit-learn; the 10-fold cross-validation accuracy score was 87.17%.

Category	Topic	Public Tweet
Expression Related	Positive	THANK YOU FOR YOUR SELFLESS SERVICE! @NYPDnews @detroitpolice @PhillyPolice @HoustonPolice @SNTONIOPNPNEPPO @SLMPD @DenverPolice @911LAPD
	Negative	This is a very bad headline, open to misinterpretations. Will the @NYPDnews realize? #NYPD #NewYork #NewYorkCity http://t.co/rXWFPJdVdv
	Strong Negative	FUCK YALL @detroitpolice ... YALL KNOW ITS FUCK YALL RIGHT!? Just making sure
Information Related	Sharing	Breaking: Man shot in West #Oakland in stable condition as @oaklandpoliceca investigate. @insidebayarea http://t.co/twlEl8vB7R
	Seeking	What is going on here @NYPDnews @deBlasioNYC @POTUS? Are these #NYPD Officers? WARNING: Disturbing video http://t.co/w6xN2xdPTG @dailykos
Action Related	General	Help this man @NYPDnews @GardaTraffic @LAPDHQ @WeightWatchers @ExtWeightLoss @SICKINDIVIDUALS

Table 2: The Code Scheme and Samples of Public Tweets

3.3 User Profile Collection and Stakeholder Classifications

To find out who was mentioned by the agencies, we extracted user names by searching "@username" in the agencies' tweets. We developed a program using Twitter's API that fetched the user profile information of both users who mentioned the agencies, and those who were mentioned by the agencies. The profile data extracted includes: the number of friends, followers, user description, and location information.

According to the salience model of stakeholder theory, we measured salience (power, legitimacy, and urgency) in terms of user popularity, locality, and job occupation. Below, we present how we evaluated salience under each measurement.

3.3.1 User Popularity. When measuring user popularity, we applied the definitions of *Reputation*, as defined by Thomas et al. [37], and the Twitter Follower-Friend (TFF or follow-to-follower) ratio [19]. A user's *Reputation* is defined as the user's number of followers divided by the sum of the user's followers and his or her friends. Prior work [37] found that normal users are likely to follow back when others follow them, thus their *Reputation* values are around 0.5. The TFF is defined as the ratio between the number of followers and the number of friends. Higher TFF values indicate more popular accounts, and it was suggested that a TFF larger than 2 might indicate more-popular Twitter users [19]. To test the two measurements, we calculated the *Reputation* score of 7,211 public users who mentioned agencies. There were 5,287 public users who had a TFF ratio of less than 2, and *Reputation* scores were around 0.5 ($Mean = 0.37, SD = 0.15$), we defined them as *less-popular*. The other 1,924 public users who had a TFF ratio larger than 2 had mean values much larger than the 0.5 score ($Mean = 0.84, SD = 0.10$), we defined them as *more-popular*. *More-popular* users have more potential to influence more users (their followers), indicating stronger power, thus *more-popular* users have more salience than *less-popular* users.

3.3.2 User Locality. We checked users' locality by comparing their location with the city location of the agency that they mentioned. If their location was the same as the agency, their user locality was tagged as *local*; otherwise, their user locality was tagged as *non-local*. As *local* users discussed or shared more relevant content (more legitimacy) and paid more attention to urgent local concerns (urgency) on Twitter [41], they were considered more salient than *non-local* users.

3.3.3 User Roles. Regarding user roles, we consulted Crump's [10] classifications of agency followers on Twitter. Considering the varying levels of power that different stakeholders can exert in the process of policy making [17], instead of grouping politicians with other public sectors such as health and education into one category, we separated them into a different category. After coding the user roles using sample user accounts, we developed the following five categories to code for classifying user roles based on their self-descriptions of their Twitter profiles:

(1) *Media* stands for organizations from the media industry such as @NYTIMES or individuals, who are identified as members of the media/media personalities such as journalists, hosts of radio shows, TV anchors, etc.

(2) *Politicians* refer to users whose occupational responsibility has direct influence on policy and governance. These include city mayors, council members, etc.

(3) *Police-affiliated* represent organizations or individual police officers that have direct affiliations with the police departments, such as officers of the agency or chiefs of police agencies.

(4) *Other sectors* represent users whose occupations do not belong to any of the above categories, such as photographers, librarians, lawyers, athletes, etc.

(5) *Not provided* indicate that the users do not provide self-description.

(6) *Not identified* mean that users' self-descriptions are not sufficient for identifying their societal roles or occupations.

The inter-coder agreement test with Cohen's Kappa on user roles was 0.77 (95% confidence interval CI: [0.66, 0.88]). The Cohen's Kappa value of individual user roles showed almost perfect agreement ($0.81 \sim 0.99$), except that *Politicians* and *Other sectors* had substantial agreement ($0.61 \sim 0.80$) [38]. We further used the annotated user roles as the foundation to classify the rest of the user descriptions using the SVM algorithm in Scikit-learn; the 10-fold cross-validation accuracy score was 71.1%.

Different occupations have different levels of salience and concerns [17]. *Media*, especially local media, has medium salience. They have their own online channels for communication. Their legitimacy is high but their power and urgency are low. *Politicians*, who are legal representatives, have high salience. They are concerned with their long-standing ambitions for positive development. Some of them also use social media to promote themselves. *Police-affiliated* users have high salience, the same as *Politicians*. *Other sectors*, *Not provided* and *Not identified* users have medium or low salience. For example, activists have medium salience because of low power. But they try to raise their power through convincing the general public.

4 FINDINGS

Using the code schemes presented above, we annotated the agency tweets, classified the public tweets and classified the involved users. In this section, we present our findings of the interactions between the 14 agencies and the public on Twitter.

Because of random sampling, the 14 agencies had different profiles on Twitter (shown in Table 3) including the account created date, number of followers, number of tweets collected (by using the Twitter API), number of favorites, number of retweets, number of mention times (the number of tweets in which the agency mentioned other Twitter accounts), and number of mentioned users (the unique number of users mentioned by the agency). We also included the number of "being mentioned", which represents the number of original tweets published by the public that mentioned one or more agencies in the message body by using "@".

Twitter Accounts	Account Created Time	Followers	Tweets Collected	Received Favorites	Received Retweets	Mention Times	Mentioned Users	Being Mentioned
New York City PD	14-Nov-08	167,000	1,469	45,062	54,792	900	272	5,688
Portland PD	30-Apr-08	52,800	1,492	7,698	9,996	386	263	1,499
San Francisco PD	28-Apr-09	46,600	291	1,811	6,084	164	57	1,889
St. Louis PD	4-Feb-10	30,000	492	3,384	4,570	264	114	1,977
Oakland PD	6-Apr-10	20,100	198	882	1,608	111	63	1,011
Cleveland PD	13-Mar-12	16,700	245	2,755	3,785	54	37	1,612
Scottsdale PD	15-Aug-08	15,400	145	924	1,981	34	30	197
Stockton PD	17-Jan-09	13,700	1,126	2,274	2,959	102	67	368
St. Paul PD	14-Aug-10	12,900	516	1,064	3,358	289	199	202
Detroit PD	24-Mar-10	9,513	262	886	823	66	68	611
Spokane PD	29-Aug-11	7,672	336	690	1,863	150	98	457
Boulder PD	14-Oct-08	7,608	317	182	330	14	11	132
Virginia Beach PD	2-Jun-09	5,437	140	301	811	7	8	212
Burlington PD	9-Oct-09	3,594	113	74	83	12	11	132

Table 3: Twitter Usage of Different Agencies.

4.1 Police Agencies Mentioning Different Stakeholders

We first present our analysis of the annotated agency tweets to better understand how agencies mentioned other users.

Agency Finding - 1 - Agencies sent significantly more *Networking* tweets than *Push* or *Pull* tweets. *Networking* tweets also received significantly more favorites than *Push* or *Pull* tweets, and received more retweets than *Push* messages. (**RQ1**)

Among the 7,142 collected agency tweets, there were 3,295 (46%) *Networking* tweets (*Appreciation*, 2.93%; *Information*, 38.57%; *Personnel*, 2.95%; *Tip*, 1.68%), 2,777 (39%) *Push* tweets (*Announcement*, 17.42%; *Crime*, 15.57%; *Traffic*, 5.89%), and 1,070 (15%) *Pull* tweets. We performed Analysis of Variance (ANOVA) to examine whether the three categories differed significantly in their received user interactions. Due to unequal sample sizes and unequal variance for each topic, we conducted Games-Howell tests [20] for post hoc pairwise comparisons. *Networking* tweets received significantly more favorites ($Mean = 13.9, SD = 48.06$) than *Push* tweets ($Mean = 6.4, SD = 16.85$, $p < 0.01$) and *Pull* tweets ($Mean = 4.1, SD = 6.86$, $p < 0.01$).

In the *Networking* tweets, *Appreciation* and *Personnel* topics received a large number of favorites. For example, an *Appreciation* tweet, "*Thank you to all for your show of support for the NYPD and the men and women of the @NYPD105Pct. http://t.co/TB4PjtWkxq*" from *NYPDnews*, received 788 favorites and 521 retweets. An *Information* tweet, "*We hope you enjoyed the @TimbersFC match tonight! Please get home safe! RCTID http://t.co/B q EHIIhRd1*" sent by *PortlandPolice* received 68 favorites and 9 retweets.

Though there was no significant difference between *Networking* ($Mean = 15.3, SD = 60.87$) and *Pull* ($Mean = 17.5, SD = 36.57$) in terms of received retweets, they received significantly more retweets than *Push* tweets ($Mean = 8.6, SD = 21.49$, $p < 0.01$).

Agency Finding - 2 - Agencies mentioned different stakeholders the most when they sent *Information* and *Appreciation* tweets, i.e., tweets with a large number of mentions per tweet. (**RQ2**)

Among the 7,142 collected tweets, agencies mentioned other user accounts in 2,553 tweets, including 1,709 *Networking*, 639 *Push* and 205 *Pull* tweets. We performed Analysis of Variance (ANOVA) to compare the number of mentions per tweet for different topics. The results showed that *Appreciation* ($Mean = 1.39, SD = 1.08$) and *Information* ($Mean = 0.83, SD = 1.03$) tweets had a significantly larger number of mentioned users than other tweets, e.g., *Personnel* ($Mean = 0.51$, $SD = 0.66$, $p < 0.001$), *Announcement* ($Mean = 0.36$, $SD = 0.74$, $p < 0.001$), *Traffic* ($Mean = 0.23$, $SD = 0.5$, $p < 0.001$), and *Request* ($Mean = 0.23$, $SD = 0.51$, $p < 0.001$).

For example, an *Information* tweet from *PortlandPolice*, "*Proud of our @ThornsFC players at the FIFAWWC @alexmorgan13 @tobinheath @stephcatley @sincy12 @nangerer @jodes14 @rhirhi8 @KaylynKyle*", mentioned 9 users who were *Not identified*. An *Appreciation* tweet, "*Thank You For A TrueBlue Night http://t.co/Lywv8kug0p @7BOOMERESIASON @cc660 @WFAN660 http://t.co/VH6WR2hw2w*" from *NYPDNews*, mentioned 3 users who were local *Media*.

Agency Finding - 3 - Overall, agencies mentioned *more-popular* user accounts than *less-popular*, especially when sending crime related information. However, when networking with the public, they had a larger percentage of appreciation and informational tweets mentioning *less-popular* users. Agencies also mentioned more local users than non-local ones. Surprisingly, regardless of the topics, the agencies mentioned *Not identified* users more than other users whose roles were defined, and mentioned *Police-affiliated* users more when sending *Crime* and *Request* tweets. (**RQ3**)

To understand when agencies mentioned different users, we examined the relationship between the topic of the agency tweet and user popularity, locality and user role respectively.

4.1.1 User Popularity.

First, among the 1,196 unique users mentioned by agencies, a total of 389 (32.5%) unique *less-popular* users were mentioned 673 times, and a total of 807 (67.5%) unique *more-popular* users were mentioned 3,077 times in agencies' tweets. According to the result of our Chi-square test of independence comparing different topics with popularity, there was also a significant interaction between the topic and user popularity ($\chi^2(7) = 88.963$, $p < 0.001$). More specifically, *more-popular* users received 9 times more mentions than *less-popular* users in *Crime* tweets, and 6 times more in *Request* tweets, but when sending *Appreciation* tweets, *more-popular* users were mentioned 1.5 times more than *less-popular* users by the agencies.

For example, in a *Crime* tweet, *PortlandPolice* mentioned the user *oregonian* - "*Mother of 24-year-old Seattle man killed in Portland speaks out: 'He didn't deserve to be gunned down' http://t.co/2e1u0XhC0Ivia@oregonian.*", and *oregonian* is a very popular local media account whose TFF was 369.01. In a *Request* tweet, *NYPDnews* mentioned *NYPD101Pct* - "*WANTED: Males for shots fired at NYPD officers, 14-20 Redfern Ave Queens 6/7, 1:45am. WATCH: https://t.co/1f1rrbc4Hl#800577TIPS @NYPD101Pct*", where *NYPD101Pct* was the official Twitter of the 101st Precinct whose TFF was 17.59. When the police agencies were seeking timely request, they addressed very popular accounts, e.g., *Media* or other *Police-affiliated* users.

4.1.2 User Location.

Second, a total of 685 unique local users were mentioned 2,287 times, and a total of 360 unique non-local users were mentioned 900 times. There were also 160 users who did not provide their location, mentioned 563 times by the agencies. A significant interaction was also found between user locality and tweet topic, according to the Chi-square test result ($\chi^2(14) = 124.023$, $p < 0.001$). More specifically, larger portions of the *Appreciation* (61%), *Announcement* (70%), *Request* (62%) and *Traffic* (82%) tweets mentioned local users. On the contrary, when sending *Personnel* tweets (54%), they mentioned non-local users more frequently.

For example, in an *Announcement* tweet, "*PLEASE RT: Spokane PD has investigated threat at Shadle Park HS determined it was NOT credible. No danger to @spokaneschools students.*", the *SpokanePD* agency mentioned *spokaneschools*, a local user who were sharing stories, information and family activities in the Spokane education community. In a *Traffic* tweet, "*SFPD Traffic Safety Video. Great video to become familiar with laws relating to walking, biking, driving http://t.co/MmPTcIyQtf @walksf @sfbike*", *SFPD* mentioned two local organization users, i.e., *walksf* and *sfbike*. The police agencies aimed to share local-related events to local organizations or communities. These accounts were more connected with the local public and were able to share information with relevant local stakeholders.

4.1.3 User Role.

Lastly, a significant interaction was also found between user role and topic according to the Chi-square test result ($\chi^2(21) = 132.26$, $p < 0.001$). Surprisingly, among the five user roles, *Not identified* users were mentioned by the agencies more frequently. More specifically, *Not identified* ($Mean = 2.65, SD = 4.63$) users were mentioned frequently in *Appreciation* (41%), *Tip* (50%), and *Traffic* (61%) tweets.

We noticed that *NYPDnews* often mentioned *Police-affiliated* users in many of their tweets. In fact, *police-affiliated* ($Mean = 7.04, SD = 18.36$) users were mentioned the most in *Crime* (49.1%) and *Request* (60%) tweets. For example, "*Great work by NYPD cops from @NYPDPSA3 for taking this illegal gun off the streets Brooklyn http://t.co/b3tPvZuGoP*" and "*@NYSPolice continue to search for Dannemora, NY prison escapees. Please call 1-800-GIVETIP with any information*" mentioned *Police-affiliated* to provide support to their police officers and to provide transparency to their community members respectively.

4.2 Different Stakeholders Mentioning Police Agencies

After manually annotating the sample public tweets, we classified the rest of the tweets into 6 topics. Among the 15,785 total tweets, public users mentioned the agencies in their *Sharing* tweets (10,182, 64.50%) the most, followed by *Negative* (2,641, 16.73%), *Positive* (1,855, 11.75%), *General* (476, 3.02%), *Strong Negative* (396, 2.51%), and *Seeking* (235, 1.49%) tweets. To understand how public users mentioned agencies, we examined the dependencies between the topic of the tweets and user popularity, locality and user roles respectively.

Public Finding - 1 - There was a larger number of *less-popular* users who mentioned the agencies than popular users; however, *less-popular* users did not tweet more frequently. *Less-popular* users tweeted more *Negative* topics and *more-popular* users tweeted more *Positive* (e.g. *emotional support*) and *Sharing* topics, as well as *Seeking* and *General* topics. (**RQ 4-a**)

First, a total of 5,287 unique *less-popular* users sent 10,145 tweets ($Mean = 1.92, SD = 4.27$) and a total of 1,924 unique *more-popular* users sent 5,640 tweets ($Mean = 2.93, SD = 7.99$). The distribution of unique users in terms of popularity within each topic showed no significant difference according to the Chi-square test result ($\chi^2(5) = 3.551, p = 0.616$). For example, 70% of the users who sent *Strong Negative* tweets were less popular, vs. 30% of the users who were more popular. We then examined the dependence between the frequency of the tweet topics and user popularity. The Chi-square test results showed that there was a significant dependence between the tweet frequency and user popularity ($\chi^2(5) = 43.84, p < 0.001$).

For example, a *more-popular* local user *jennbisramtv* ($TFF = 80.34$) tweeted "Detroit PD need your help in finding this 6-month old baby; suspect wanted on warrant. @detroitpolice @wxyzdetroit http://t.co/sOo8BTkX31". This tweet included specific details about the lost child and the suspect. In contrast, a *less-popular* ($TFF = 1.58$) *not identified* user called *msofka* tweeted "Please help @cavs @PDcavsinsider @cavsdan @CavsNtn @CLEsportsTalk @EngageCleveland @CLEpolice @Q104Cleveland @Browns" without giving the details of the request explicitly.

Public Finding - 2 - In general, local users tweeted more frequently than non-local users. Local users' tweets were more *Positive*, *General* and *Seeking* compared to non-local users' tweets where more negative topics, i.e., *Strong Negative* and *Negative* (anti-social or criticizing) topics were mentioned. (**RQ 4-b**)

A total of 3,009 unique local users sent 7,856 tweets ($Mean = 2.61, SD = 6.56$), and a total of 2,940 unique non-local users sent 5,398 tweets ($Mean = 1.84, SD = 4.30$), while a total of 1,339 unique users with not specified location sent 2,531 tweets ($Mean = 1.89, SD = 3.95$). We also examined the dependence between user locality and the topics they tweeted about. Our Chi-square tests showed that there was a significant dependence between user locality and tweet topics ($\chi^2(5) = 86.496, p < 0.001$). There was also a significant dependence between user locality and tweet frequency ($\chi^2(5) = 168.574, p < 0.001$).

More specifically, *Positive* (880 v.s. 664), *Seeking* (104 v.s. 81) and *General* (203 v.s. 177) tweets were sent by more local users than non-local users. Local users sought more specific information which was about their daily life.

For example, a local user in New York sent a tweet seeking information about Central Park: "*Why is there a wall of fencing around Central Park? @CentralParkNYC @HelenRosenthal @NYPDnews http://t.co/aM3xJEa2Ue*." We also randomly sampled *Seeking* tweets sent by non-local users and found that non-local users tweeted more about general questions.

On the other hand, non-local users tweeted more *Strong Negative* and *Negative* topics ($p < 0.001$). We reviewed the *Strong Negative* and *Negative* tweets sent by non-local users, who tended to only express their negative emotions to police agencies. However, most of the tweets didn't contain specific topics addressed by their tweets, e.g., arrest, traffic, etc.

Public Finding - 3 - *Not Identified* users tweeted the most across all topics. (**RQ 4-c**)

Among the 15,785 total public tweets, 7,244 (45.89%) were sent by *Not identified* users, followed by 3,815 (24.17%) tweets from *Media* users, 2,676 (16.95%) tweets from *Other sectors*, 1,042 (6.60%) tweets from *Not provided* users, 762 (4.83%) from *Police-affiliated* users, and 246 (1.56%) from *Politicians*. A significant interaction was also found between user roles and tweet frequency of different topics according to the Chi-square test result ($\chi^2(25) = 1,383.3$, $p < 0.001$).

More specifically, *Not identified* users sent 3.98% *Strong Negative*, 21.11% *Negative*, 11.94% *Positive*, 3.67% *general*, 1.99% *Seeking*, and 57.32% *Sharing* tweets. Some *Not identified* users may send tweets specific details of which deserve agencies to pay more attention. For example, a female user created a 50-page slideshow as evidence to support her criticism that local police paid less attention to and not enough effort in solving local homicide cases with female victims, particularly when the victims were black. The user's local police mentioned her when replying to her questions regarding whether there were any rewards for providing information related to crime investigations. She was known by other activists; as others mentioned her when sharing cases where black women were injured.

In another instance, a male web developer sent a *Strong Negative* tweet when his Twitter account was blocked by the local police. Meanwhile, he had sent 84 tweets mentioning the agency, and most of his tweets seemed to provide online and offline support to his police agency, e.g., *"Congrats @PortlandPolice @BikeIndex @BikePortland @project529 http://t.co/ugFoWUIpg3 http://t.co/4os3KEgaz5"*, and shared information for safety *"Bikes and Trikes accumulating at camps on NW Side of steel bridge. @PortlandPolice @PPBBikeTheft @MayorPDX"*. Compared to other users who only sent *Strong Negative* tweets, this user clearly was trying to build a positive and strong relationship with the local police agency. When this user sent a *Strong Negative* tweet, there was a specific reason why the user did so, which might need the agency's attention and response.

5 DISCUSSION

In this section, we reflect on our findings and discuss the implications for police agencies' use of social media for community policing.

5.1 Understanding Agencies' Social Media Strategies

Our findings contribute new knowledge about how police agencies and the public interact on Twitter to support community policing. First, we found that the government agencies not only used *Push* or *Pull* strategies, but also used an interactive mingling strategy [23]. By focusing on the mention behaviors on Twitter, our findings suggest that the studied law enforcement agencies use social media more for building relationships with users rather than simply for *Pull* or *Push* purposes.

Our sample tweets indicated that police agencies could explicitly express their requests to their stakeholders by adding "RETWEET!" to receive more retweets (**Agency Finding 1**). The agencies also effectively engaged stakeholders by expressing appreciation of them or communicating with them individually regardless of the user's social status. (**Agency Finding 2**).

Our findings also suggest that the agencies engaged different stakeholders for varying purposes. For example, when requiring a more immediate reaction, e.g., when disseminating crime investigation requests, the agencies mentioned *more-popular* users (those who had more followers on Twitter) and *Police-affiliated* users (**Agency Finding 3**), which can be explained by the stakeholder theory [25]. In our case, crime investigation requests need urgent responses. Since popular users on social media have more followers, i.e. politicians (with more power, legitimacy and urgency) and media users (with more legitimacy), mentioning them can potentially allow more public users to receive the information faster.

Compared to other users, *Police-affiliated* users (including police officers from within the law enforcement infrastructure) could also easily justify their legitimacy, which might explain why they were mentioned more in *Crime* and *Request* tweets. We also found that the agency tweets that mentioned these stakeholders received more favorites and retweets.

However, stakeholder theory framework might not be sufficient to explain the finding that the agencies mentioned *Not identified* users frequently, because *Not identified* users, especially those *less-popular* ones, may not have much power or an established legitimate relationship with the agencies. These users were mentioned frequently in tweets, such as *Appreciation* and *Information* tweets in the *Networking* strategy that were not mission critical or urgent. After studying a few hundred tweets, we found that when an agencies mentioned the *Not identified* users, they usually answered questions raised by the user(s) or simply thanked the user(s) for providing helpful safety-related information. Since *Networking* tweets are used to promote long-term relationships and to promote the image of the agencies, this finding may suggest that the agencies mentioned the users for creating a good public image as being responsive. In this case, a stakeholder's value is associated with his or her potential to support the long-term mission of community policing; although they may lack of social power or raise legitimate concerns related to community policing.

5.2 Understanding Stakeholders on Social Media

Our results regarding how the public mentions police agencies provided some interesting insights for community policing on Twitter. Previous work noted that stakeholders with less salience are more likely to participate on social media and "will use every available medium to gain influence" [17]. This may help explain our finding that *less-popular* users mentioned agencies more and tweeted more negative topics (**Public Finding 1**) and *Non-identified* users tweeted the most (**Public Finding 3**), possibly for more attention on social networks.

Because community policing is usually bound to certain physical geographic locations [34], local users participated more by sending supporting messages and more actionable requests (**Public Finding 2**) for reciprocal benefits, e.g., enhancing local safety. On the other hand, the tweets from non-local users seemed to be driven more by the national trend of criticizing police brutality rather than actual concerns about local issues like public safety. There was also a very limited number of tweets sent by non-local users regarding crime solving or prevention. This could be due to the fact that non-local users might not be familiar with local situations.

5.3 Implications

We drew from stakeholder theory [25] to explain how users and police agencies interacted using mentions on Twitter. Given the rapid growth of interactions on social media, police agencies have a pressing need to better leverage the network intelligence and deal with various stakeholders online. Recently a tension monitoring tool was suggested to be created for analyzing signs on the networks that can help predict public disorder [39]. Our results provided more insights to the design of such monitoring tools. Our proposed three code schemes and the measurement of stakeholder salience can also be used to devise algorithms for assessing the value of potential stakeholders.

The emergent social media networks augmented the policing in "cyber-neighborhoods" compared to previously when they usually interacted with local communities [39]. Our findings also suggested that agencies should not be overwhelmed by a large number of negative tweets, because the majority could be from non-local users who simply complain without knowing the local practice well. Prioritizing the tweets based on the locality of the social media users (local tweets first) may be an effective way to handle the tweets. Enough attention should also be given to those tweets that are sent by *Not identified* users on social media.

5.4 Limitations and Future Work

We only looked at the headquarter accounts of these police agencies. The data set we used for this study consisted of tweets from 14 municipal police agencies in the U.S. and public mention tweets within 6 months in 2015. It is likely that the agencies adapted their behaviors on Twitter during this time for public relations purposes. We focused on daily usage of social media during non-crisis situations. Thus, the findings may not be applicable in crisis situations. In our future work, we plan to re-evaluate the findings using more agencies' data, as well as to compare interactions between regular and crisis situations.

6 CONCLUSION

Police agencies have started using social media to build community policing, i.e., to establish collaboration between the people in a community and local police departments. Both researchers and practitioners need to understand the daily interactions between agencies and different stakeholders on social media so that effective strategies or tools can be developed for agencies to better fulfill their missions. We analyzed the tweets from 14 agencies and public users through the lens of stakeholder theory. We shared new understandings of police agencies' social media strategies, design implications for system designers, and practical implications for building community policing on Twitter.

7 ACKNOWLEDGEMENT

This material is based upon work supported by the National Science Foundation under Grant No.1464312. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

REFERENCES

[1] 2014. Survey on Law Enforcement's Use of Social Media. (2014). http://www.iacpsocialmedia.org/Resources/Publications/2014SurveyResults.aspx [Online; accessed 22-September-2015].
[2] Jerry Abramson. 2015. 10 Cities Making Real Progress Since the Launch of the 21st Century Policing Task Force. (2015).
[3] Fuat Altunbas. 2014. Social Media in Policing: a Study of Dallas-fort Worth Area City Police Departments. (2014).
[4] Karin Axelsson, Ulf Melin, and Ida Lindgren. 2013. Public e-services for agency efficiency and citizen benefit-Findings from a stakeholder centered analysis. *Government Information Quarterly* 30, 1 (2013), 10–22.
[5] Enrique Bonsón Ponte, Elena Carvajal-Trujillo, and Tomás Escobar-Rodríguez. 2015. Corporate Facebook and stakeholder engagement. *Kybernetes* 44, 5 (2015), 771–787.
[6] Lori Brainard and Mariglynn Edlins. 2015. Top 10 US Municipal Police Departments and Their Social Media Usage. *The American Review of Public Administration* 45, 6 (2015), 728–745.
[7] Axel Bruns, Jean E. Burgess, Kate Crawford, and Frances Shaw. 2012. #qldfloods and @QPSMedia: Crisis Communication on Twitter in the 2011 South East Queensland Floods. (January 2012).
[8] David A. Campbell, Kristina T. Lambright, and Christopher J. Wells. 2014. Looking for Friends, Fans, and Followers? Social Media Use in Public and Nonprofit Human Services. *Public Administration Review* 74, 5 (2014), 655–663.
[9] Community Policing Consortium, Publicity Manager, and United States of America. 1994. Understanding Community Policing: A Framework for Action. (1994).
[10] Jeremy Crump. 2011. What are the police doing on Twitter? Social media, the police and the public. *Policy & Internet* 3, 4 (2011), 1–27.
[11] Sebastian Denef, Petra S Bayerl, and Nico A Kaptein. 2013. Social media and the police: tweeting practices of British police forces during the August 2011 riots.

In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 3471–3480.
[12] Leif Skiftenes Flak and Jeremy Rose. 2005. Stakeholder governance: Adapting stakeholder theory to e-government. *Communications of the Association for Information Systems* 16, 1 (2005), 31.
[13] R Edward Freeman. 2010. *Strategic management: A stakeholder approach*. Cambridge University Press.
[14] Stephan G. Grimmelikhuijsen and Albert J. Meijer. 2015. Does Twitter Increase Perceived Police Legitimacy? *Public Administration Review* 75, 4 (2015), 598–607.
[15] Youyang Hou and Cliff Lampe. 2015. Social Media Effectiveness for Public Engagement: Example of Small Nonprofits. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 3107–3116.
[16] Yun Huang, Sen Huo, Yaxing Yao, Niu Chao, Yang Wang, Jennifer Grygiel, and Steve Sawyer. 2016. Municipal Police Departments on Facebook: What Are They Posting and Are People Engaging?. In *Proceedings of the 17th International Digital Government Research Conference on Digital Government Research*. ACM, 366–374.
[17] Marius Rohde Johannessen, Øystein Sæbø, Leif Skiftenes Flak, and Zahir Irani. 2016. Social Media as Public Sphere: A Stakeholder Perspective. *Transforming Government: People, Process and Policy* 10, 2 (2016).
[18] Till Keyling and Jakob Jünger. 2013. Facepager (Version, fe 3.3). An application for generic data retrieval through APIs. (2013).
[19] Kyle Lacy. 2011. *Twitter Marketing for Dummies*. John Wiley Sons.
[20] Alexander Leichtle. 2012. The Games-Howell Test in R. (2012). http://www.gcf.dkf.unibe.ch/BCB/files/BCB_10Jan12_Alexander.pdf Retrieved October 1st 2012 from.
[21] Kristen Lovejoy and Gregory D Saxton. 2012. Information, community, and action: How nonprofit organizations use social media. *Journal of Computer-Mediated Communication* 17, 3 (2012), 337–353.
[22] Albert Meijer and Marcel Thaens. 2013. Social media strategies: Understanding the differences between North American police departments. *Government Information Quarterly* 30, 4 (2013), 343–350.
[23] Ines Mergel. 2012. The social media innovation challenge in the public sector. *Information Polity* 17, 3, 4 (2012), 281–292.
[24] Ines Mergel. 2013. A framework for interpreting social media interactions in the public sector. *Government Information Quarterly* 30, 4 (2013), 327–334.
[25] Ronald K. Mitchell, Bradley R. Agle, and Donna J. Wood. 1997. Toward a Theory of Stakeholder Identification and Salience: Defining the Principle of Who and What Really Counts. *The Academy of Management Review* 22, 4 (1997), 853–886.
[26] Christopher D. O'Connor. 0. The police on Twitter: image management, community building, and implications for policing in Canada. *Policing and Society* 0, 0 (0), 1–14.
[27] Yan Qu, P. F. Wu, and Xiaoqing Wang. 2009. Online Community Response to Major Disaster: A Study of Tianya Forum in the 2008 Sichuan Earthquake. In *System Sciences, 2009. HICSS '09. 42nd Hawaii International Conference on*. 1–11.
[28] Dennis P Rosenbaum, Lisa M Graziano, Cody D Stephens, and Amie M Schuck. 2011. Understanding community policing and legitimacy-seeking behavior in virtual reality: A national study of municipal police websites. *Police Quarterly* 14, 1 (2011), 25–47.
[29] Niharika Sachdeva and Ponnurangam Kumaraguru. 2015. Characterising Behavior and Emotions on Social Media for Safety: Exploring Online Communication between Police and Citizens. *arXiv preprint arXiv:1509.08205* (2015).
[30] Øystein Sæbø, Leif Skiftenes Flak, and Maung K Sein. 2011. Understanding the dynamics in e-Participation initiatives: Looking through the genre and stakeholder lenses. *Government Information Quarterly* 28, 3 (2011), 416–425.
[31] Matthew C Scheider, Robert Chapman, and Amy Schapiro. 2009. Towards the unification of policing innovations under community policing. *Policing: An international journal of police strategies & management* 32, 4 (2009), 694–718.
[32] Hans J Scholl. 2004. Involving salient stakeholders Beyond the technocratic view on change. *Action Research* 2, 3 (2004), 277–304.
[33] Kristina Sedereviciute and Chiara Valentini. 2011. Towards a More Holistic Stakeholder Analysis Approach. Mapping Known and Undiscovered Stakeholders from Social Media. *International Journal of Strategic Communication* 5, 4 (2011), 221–239.
[34] Wesley G Skogan and Susan M Hartnett. 1997. *Community policing, Chicago style*. Oxford University Press New York.
[35] Brian G Smith. 2010. Socially distributing public relations: Twitter, Haiti, and interactivity in social media. *Public Relations Review* 36, 4 (2010), 329–335.
[36] Liyang Tang, Zhiwei Ni, Hui Xiong, and Hengshu Zhu. 2015. Locating targets through mention in Twitter. *World Wide Web* 18, 4 (2015), 1019–1049.
[37] Kurt Thomas, Chris Grier, Dawn Song, and Vern Paxson. 2011. Suspended Accounts in Retrospect: An Analysis of Twitter Spam. In *Proceedings of the 2011 ACM SIGCOMM Conference on Internet Measurement Conference (IMC '11)*. ACM, New York, NY, USA, 243–258.
[38] Anthony J Viera, Joanne M Garrett, et al. 2005. Understanding interobserver agreement: the kappa statistic. *Fam Med* 37, 5 (2005), 360–363.
[39] Matthew L. Williams, Adam Edwards, William Housley, Peter Burnap, Omer Rana, Nick Avis, Jeffrey Morgan, and Luke Sloan. 2013. Policing cyber-neighbourhoods: tension monitoring and social media networks. *Policing and Society* 23, 4 (2013), 461–481.
[40] Weiai Xu. 2015. *Predicting Social Capital in Nonprofits' Stakeholder Engagement on Social Media*. Ph.D. Dissertation. STATE UNIVERSITY OF NEW YORK AT BUFFALO.
[41] Sarita Yardi and Danah Boyd. 2010. Tweeting from the Town Square: Measuring Geographic Local Networks.. In *ICWSM*.