Understanding Interactions Between Municipal Police Departments and the Public on Twitter

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Abstract. Law enforcement agencies have started using social media for building community policing, i.e., establishing collaborations between the people in a community and local police departments. Both researchers and practitioners need to understand how the two parties interact on social media on a daily basis, such that effective strategies or tools can be developed for the agencies to better leverage the platforms to fulfill their missions. In this paper, we collected 9,837 tweets from 16 municipal police department official Twitter accounts within 6 months in 2015 and annotated them into different strategies and topics. We further examined the association between tweet features (e.g., hashtags, mentions, content) and user interactions (favorites and retweets) by using regression models. The models reveal surprising findings, e.g., that the number of mentions has a negative correlation with favorites. Our findings provide insights into how to improve interactions between the two parties.

1 Introduction

Social media (e.g., Facebook, Twitter, etc.) in government is a trending topic in both research and real practice [6]. Law enforcement agencies have realized that social media can be used to fulfill their organizational missions [26]. According to a survey by the International Association of Chiefs of Police (IACP), social media was used by more than 95% of 600 law enforcement agencies surveyed in 2014 [1]. Social media platforms allow people to share information instantly and facilitate mutual interactions, which enable police agencies to handle crimes more effectively and to promote the reciprocal relationship between police and the community [8,25]. Thus, an increasing number of municipal police departments intentionally try to employ social media for building community policing [2,14]. The idea of community policing is to develop collaborations between the people in a community and local police departments, resulting in solving issues and improving public safety together [5].

In order to effectively involve the community in regular daily operations [22], it is necessary to understand the day-to-day social media practices of law enforcement agencies [5]. Interview-based studies provide a great deal of information

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that enables us to learn about how social media is used by law enforcement agencies, where different combinations of strategies are employed by law enforcement agencies to represent, engage, and network [22,23]. While valuable, these studies lack profound insights into what topics law enforcement agencies really tweet about on social media everyday and what topics users interact with the most. Models and tools are suggested to be built for better understanding of social media interactions [3]. On Twitter, such interactions can be measured in the form of favorites and retweets [16].

In this paper, we address the above research needs by examining the tweets of 16 municipal police departments in the U.S. We unpack police agencies' tweeting behavior and public interactions. Reflecting on our findings, we provided practical suggestions on how the agencies could improve interactions with their communities on social media.

2 Related Work

Law enforcement agencies have started using social media applications to broadcast information such as events, crime, traffic and safety, and to disseminate information to a large audience in a timely and accurately manner [11]. They also use social media to respond to the public's inquiries about incidents [4,7]. To describe how agencies interact with the public, researchers developed a framework consisting of three social media strategies, i.e., *Push*, *Pull* and *Networking* [22,23]. They found that agencies intended to use different combinations of these strategies. More specifically, when a *Push* strategy is applied, social media sites are used as an additional communication channel "to get the message out." Compared with *Push* (an one-way strategy to provide transparency), *Pull* is a two-way strategy with the goal of engaging the public by soliciting information or requesting certain actions. The *Networking* strategy, emphasizing the collaboration between the government agencies and the public, is also to promote a two-way interaction.

Researchers have studied how a variety of factors (e.g., length, hashtag, URL, topic, etc.) could impact user interactions [15,24,27,31,32]. For example, Suh et al. [31] tried to identify factors that influenced the retweetability of a user's tweet so that a prediction of the retweetability could be made; they found that URLs and hashtags as content features, numbers of followers and followees and age of accounts as contextual features are considered to have a strong correlation with the retweetability of a tweet. Vargo [32] also presented similar findings that the presence of hashtags boosted the retweet and favorite counts, while Petrovic et al. [27] proved that the number of followers and followees of the sender had correlation with retweetability. Naveed et al. [24] considered that the tweet topics affected the retweetability; they identified 100 topics in tweets and found that tweets with general topics or interests, such as social media, economy, Christmas and public events, were more likely to be retweeted, while tweets in specific or individual topics were less likely to be retweeted.

In our work, we apply the framework of three social media strategies, i.e., *Push*, *Pull* and *Networking* [22,23] to annotate agency tweets. In addition, to understand how the agencies used different strategies and the effectiveness of the strategies, we further examined agency tweets into several topics and received interactions from public users. Our work enriches the framework by materializing these three social strategies with different tweet topics.

3 Data Collection and Method

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

We searched municipal police departments' Twitter accounts in the cities that either ranked in the top 50 most populated cities of the U.S. or ranked top 10 for high crime rates as these police departments are more likely to tweet safety-related events or topics in their community. Since not all of the departments have verified Twitter accounts, we found 52 official accounts and randomly selected 16 of them for analysis. We used Facepager [20] to collect tweets and Twitter REST API to collect interactions (i.e., favorite, retweet) these tweets received. Finally, 9,837 tweets in total sent by these 16 police departments with interactions between February 17 and August 13, 2015 were collected. Table 1 shows the account names, time of account creation, the number of followers (observed by August 13, 2015), the number of tweets that were sent by each account, the number of favorites and retweets received by these tweets.

Table 1. Basic information of the police departments' (PDs) Twitter accounts, their tweets and received interactions.

Twitter accounts	Account created time	Followers	Tweets collected	Received favourites	Received retweets
Los Angeles PD	2-Sep-07	11,500	320	373	338
Portland PD	30-Apr-08	52,800	1,492	7,698	9,996
Scottsdale PD	15-Aug-08	15,400	145	924	1,981
Boulder PD	14-Oct-08	7,608	317	182	330
New York City PD	14-Nov-08	167,000	1,469	45,062	54,792
Stockton PD	17-Jan-09	13,700	1,126	2,274	2,959
Baltimore PD	27-Feb-09	134,000	2,375	64,732	124,621
San Francisco PD	28-Apr-09	46,600	291	1,811	6,084
Virginia Beach PD	2-Jun-09	5,473	140	301	811
Burlington PD	9-Oct-09	3,594	113	74	83
St. Louis PD	4-Feb-10	30,000	492	3,384	4,570
Detroit PD	24-Mar-10	9,513	262	886	823
Oakland PD	6-Apr-10	20,100	198	882	1,608
St. Paul PD	14-Aug-10	12,900	516	1,064	3,358
Spokane PD	29-Aug-11	7,672	336	690	1,863
Cleveland PD	13-Mar-12	16,700	245	2,755	3,785

In order to understand the departments' tweets, we manually annotated all the tweets based on a two-tier code scheme in our previous work [18]. The first tier codes are three strategies which police departments utilized on social media, i.e., *Push*, *Pull* or *Networking* [22,23]. The second tier codes are 8 specific topics. The definition of topics are described briefly as below.

- 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 are related 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.
- Within the ***Networking*** category, *Tip* defines tweets that communicate suggestions to improve public safety and to avoid potential dangers. *Personnel* defines tweets that address individual names of police department personnel. *Appreciation* defines tweets that express gratitude and appreciation. *Information* includes all other non-tip, non-personnel, and non-appreciation tweets. Unlike *Announcement* of the *Push* category about public safety alerts, *Information* of the *Networking* category is used to reach out to the public for building a long-term trust or relationship, e.g., for announcing a workshop for a safety-related topic.
- Within the ***Pull*** category, *Request* defines tweets that ask the public to provide information about critical issues, such as identifying a crime incident or finding a missing person.

We hired three coders and trained them to understand the coding rules and concepts. Two coders independently annotated the tweets into the first coding level. For each code in the first level, Cohen's Kappa [33] showed almost perfect agreement (0.81–0.99). We then asked the third coder to annotate the tweets independently where the first two coders had disagreed and to resolve the disagreement using the "majority rule" approach. Three coders then labeled the tweets into the second coding level using the same methodology. For *Traffic*, *Appreciate*, *Crime*, and *Request* in the second level, Cohen's Kappa also showed perfect agreement (0.81–0.99); for other codes in the second coding level, Cohen's Kappa showed substantial agreement (0.61–0.80).

4 Findings

In this section, we applied a variety of statistical methods to unfold the 16 police departments' tweeting behavior (e.g., tweeting volumes, strategies and topics), public interaction behavior (favorites and retweets), and their relationships.

4.1 Police Departments' Tweets and Interactions

We summarized the number of tweets and the number of favorites and retweets received for different tweet topics in Table 2. The descriptive statistics indicate that certain tweets received more interactions, e.g., *Personnel* received the largest favorites.

To examine the differences, we performed Multivariate Analysis of Variance (MANOVA) tests. Due to unequal sample sizes and unequal variances for different topics, we conducted Games-Howell tests [21] for post-hoc pair-wise comparisons. In terms of **favorites**, *Networking* ($M = 16.3$, $SD = 64.30$) received significantly more interaction than *Push* ($M = 13.4$, $SD = 43.21$, $df = 7,548$, $p < .01$) and *Pull* ($M = 5.1$, $SD = 43.21$, $df = 4,747$, $p < .001$); *Push* ($M = 13.4$, $SD = 43.21$) received significantly more interaction than *Pull* ($M = 5.1$, $SD = 43.21$, $df = 5,019$, $p < .001$). In terms of **retweets**, there was no significant difference between *Push* ($M = 28$, $SD = 102.33$) and *Pull* ($M = 24$, $SD = 53.12$, $df = 4,470$, $p = .11$); *Networking* received significantly less interaction than *Push* ($M = 28$, $SD = 102.33$, $df = 6,948$, $p < .001$) and *Pull* ($M = 24$, $SD = 53.12$, $df = 2,673$, $p < .001$).

Table 2. Descriptive statistics of received favorites and retweets for different categories and topics of police departments' tweets

Category	Topic	Total tweets	Favorites		Retweets	
			Mean	SD	Mean	SD
Push	Crime	1,793	10.96	27.19	19.53	60.32
	Traffic	584	7.57	15.74	11.27	38.03
	Announcement	1,804	17.60	58.97	39.85	141.23
	Information	3,519	13.42	48.38	12.58	38.56
Networking	Appreciation	308	24.82	89.24	21.12	88.52
	Tip	195	7.89	10.84	11.27	13.53
	Personnel	280	50.22	154.93	56.61	181.11
Pull	Request	1,354	5.12	8.50	23.72	53.12

Prior research found that emotion was critical to information seeking and sharing across social media [17]. When people feel emotionally connected to the social media messages, they are more likely to actively share these messages, accelerating the information dissemination process. *Networking* tweets, e.g. *Appreciation* and *Personnel*, showed that the police departments cared about their community or their police officers, which could trigger emotional connections, and therefore received more interactions.

We also performed clustering algorithms to partition the 16 police departments into clusters where police departments of each cluster share some common features. Each police department was represented as a three-dimensional vector, consisting of tweeting frequency for each category (*Push*, *Pull*, and *Networking*). For example, the frequency of *Push* is the count of *Push* tweets divided by the number of days. We applied the complete-linkage hierarchical clustering algorithm [19] and found that the optimum number of clusters was three by performing the canonical correlation analysis [9]. The first canonical dimension is strongly influenced by *Pull* (0.99) and *Networking* (0.80); the second canonical dimension is strongly influenced by *Push* (0.80). The results showed that cluster 1 included Baltimore PD and Portland PD where more *Push* tweets were sent; cluster 2 included NYPD and Stockton PD where more *Networking* tweets were sent; and the rest were grouped in cluster 3 where *Push* and *Networking* tweets were well balanced. All three clusters rarely used *Pull* strategies.

To examine if certain clusters received significantly more interactions than others, we conducted two univariate Analysis of Variance (ANOVAs) in terms of favorites and retweets. Due to unequal sample sizes and unequal variances, we performed the multiple pairwise comparisons by using the Games-Howell test [21] for the posthoc tests. To account for police departments' varying numbers of followers, we divided the number of interactions for a tweet by the total number of followers of the police department. In terms of **favorites**, cluster 3 ($M = 0.026$, $SD = 6.4E - 3$) received significantly more favorites than cluster 2 ($M = 0.019$, $SD = 2.3E - 3$, $df = 5,640$, $p < .001$); and cluster 2 ($M = 0.019$, $SD = 2.3E - 3$) received significantly more than cluster 1 ($M = 0.011$, $SD = 1.3E - 3$, $df = 3,809$, $p < .001$). In terms of **retweets**, cluster 3 ($M = 0.050$, $SD = 3.6E - 2$) received significantly more retweets than cluster 2 ($M = 0.024$, $SD = 3.6E - 3$, $df = 4,220$, $p < .001$); cluster 2 ($M = 0.024$, $SD = 3.5E - 3$) received significantly more than cluster 1 ($M = 0.014$, $SD = 1.5E - 3$, $df = 4,033$, $p < .001$). The results suggested that those police departments in cluster 3 that balanced their use of the *Push* strategy and *Networking* strategies received more interactions from the public.

4.2 Influential Factors for Interactions

In this section, by building regression models, we present several significant factors we identified in police departments' tweets, which influenced public interactions (favorites and retweets).

Factors' Selection and Regression Models. According to the reviewed literature, we initially selected a set of factors, e.g. hashtags, URLs, the length of tweets, the number of followers, tweet category, etc., and added mentions as a new factor. Then for each factor with the outcome variables (*Favorites* and *Retweets*), we ran a non-parametric Spearman's Rank Correlation Coefficient Test [28]. The test results showed that there were significant correlations between five factors (i.e., *Hashtags*, *Mentions*, *Followers*, *Days* and *Category*) and the outcome variables (*Favorites* and *Retweets*) ($p < .01$).

More specifically, the first four factors are numeric: *Hashtags* represents the number of hashtags (#) in the tweet; *Mentions* represents the number of mentions (@) in the tweet; *Followers* is the total number of followers of the police department when the police department sends the tweet; and *Days* represents the number of days between the account created date and the tweet created date. *Category* is a categorical variable, which represents the content feature of the tweet, i.e., *Push*, *Pull*, *Networking*.

We first performed a Grubbs' test to examine whether there were any outlier tweets in terms of favorites and retweets that may skew our models [13,29]. We removed 530 favorite outliers and 557 retweet outliers that accounted for about

5% of our data set. Then, we used the Negative Binomial Regression models [12] to investigate the associations between these influential factors and interactions. To build regression models, we took *Category* as a dummy variable [10] as there are three options, i.e. *Push*, *Pull*, *Networking*. For instance, for the *Push* category, D1 = 1 and D2 = 0; for the *Pull* category, D1 = 0 and D2 = 1; for the *Networking* category, D1 = 0 and D2 = 0. The two-way interactions between independent variables (e.g., *Hashtags* * *Mentions*, etc.) were also taken into consideration but no significant associations were found. As shown in Table 3, we separated three conditions of the *Category* variable into different models, i.e., FH (favorite-push), FL (favorite-pull), FN (favorite-networking), RH (retweet-push), RL (retweet-pull), RN (retweet-networking), and presented all the significant factors which impacted *Favorite* and *Retweets* ($p < .001$).

Table 3. The coefficients of significant factors for user interactions: H - Hashtags, M - Mentions, F - Followers, D - Days, FH - the model for Favorites and Push category, etc. The selected terms' coefficients in the above models all have $p < .001$.

Model	Favorites			Retweets		
	FH	FL	FN	RH	RL	UN
Intercept	1.9535	2.5219	2.1054	3.3864	4.2863	2.3940
H	0.1582	−0.0929	0.1648			
M	−0.5223	−0.1250	−0.3566			
F	0.1890	0.1947	0.3347	0.1696	0.1965	0.1272
D	−0.2510	−0.4493	−0.1732	−0.4508	−0.5535	−0.2037

Understanding the Factors. Table 3 revealed interesting observations. First, for *Favorites*, the coefficients of *Hashtags* varied from positive to negative for different categories of tweets; *Mentions* consistently had negative coefficients, and had strong coefficients under the *Push* and *Networking* models. Secondly, *Hashtags* and *Mentions* were not significantly related to *Retweets*. Below, we present further data analyses for *Hashtags* and *Mentions* that help explain the observations.

Hashtags. Prior work reported that the presence of *Hashtags* was associated with more *Retweets* [32], and it was also pointed out that not all *Hashtags* could improve the tweets popularity [31]. In *Favorites*, *Hashtags'* coefficients were positive for the *Push* and *Networking* categories, but negative for the *Pull* category. It indicated that certain *Hashtags* in *Push* and *Networking* tweets could be popular ones. Having examined the tweets, we identified that Baltimore PD's #communitypolicing and #BPDNeverForget, and NYPD's #happeningnow and #happeningsoon received the largest number of favorites. It was interesting that *Pull* tweets were negatively correlated with *Hashtags*. Having examined the data, we found that the tweets that received the largest number of favorites did not have *Hashtags*. However, many of them had the following words: REWARD, WANTED, MISSING PERSON, which usually were capitalized and appeared at the beginning of the tweets. This suggested that if the police departments used these capitalized terms in *Hashtags*, then potentially the relationships between *Hashtags* and *Favorites* might be consistent across all categories, because *Hashtags* increased message exposure by specifying content in metadata [30].

Mentions. That *Mentions* has consistent negative coefficients for *Favorites* is a surprising result. Intuitively, tweets with *Mentions* may draw more attention and subsequently receive more interactions. When we compared different topics, *Personnel* tweets received the most interactions. We suspected that those tweets would have many *Mentions*. However, when we reviewed the statistics of *Personnel* tweets, we found these tweets had significantly less number of *Mentions* ($M = 0.38$, $SD = 0.63$) than *Information* tweets ($M = 0.80$, $SD = 1.01$, $df = 390$, $p < .001$) whereas there were significantly more *Information* tweets than *Personnel* tweets ($X^2 = 3,420$, $df = 1$, $p < .001$). This may help us understand why *Mentions* had negative coefficients.

5 Discussion and Future Work

There have been extensive studies on how different factors are associated with interactions on Twitter. Our findings suggested actionable items that the police departments could consider to take so as to improve user interactions on Twitter. For example, our annotation results and clustering analyses showed that certain tweet topics (e.g., *Networking* tweets addressing *Personnel* or expressing *Appreciation*) were received more favorites; and balancing different types of tweets such as sending a similar number of *Push* and *Networking* tweets could improve user interactions than only pushing information on Twitter. Our findings revealed that hashtags and mentions could be used more effectively when combined with social media categories/topics. The use of the hashtag #communitypolicing receiving more interactions also indicated that police departments could leverage social media to implement community policing.

In this study, we started with 16 municipal police Twitter accounts from highly populated cities or high crime rated ones in the U.S. that may have more safety related issues, thus the findings may not be applied to those small cities that have significantly less safety issues. In our future work, we plan to evaluate our findings in more diverse contexts, e.g., across different countries or at different times (crisis and normal times).

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