Policing engagement via social media

Policing Engagement via Social Media

Miriam Fernandez, A. Elizabeth Cano, Harith Alani

Knowledge Media Intitute, The Open University. Walton Hall, Milton Keynes, MK76AA
{m.fernandez, amparo.cano, h.alani}@open.ac.uk

Abstract. Social Media is commonly used by policing organisations to spread the word on crime, weather, missing person, etc. In this work we aim to understand what attracts citizens to engage with social media policing content. To study these engagement dynamics we propose a combination of machine learning and semantic analysis techniques. Our initial research, performed over 3,200 posts from @dorsetpolice Twitter account, shows that writing longer posts, with positive sentiment, and sending them out before 4pm, was found to increase the probability of attracting attention. Additionally, posts about weather, roads and infrastructures, mentioning places, are also more likely to attract attention.

Keywords: Social Web, Semantic Web, Engagement, Police

1 Introduction

Social media is now commonly used to help communicate policing messages to the general public. Many forces have staff dedicated to this purpose and to improve the spreading of key messages to wider social media communities. However, while guidance reports claim that social media can enhance the reputation and accessibility of police staff to their communities [5], research studies have shown that exchanges between the citizens and the police are infrequent. Social media works as an extra channel for delivering messages but not as a mean for enabling a deeper engagement with the public. [2]

Studies targeting citizen engagement towards police forces in social media have been mainly focused on studying the different social media strategies that police forces use to interact with the public [2, 3, 5, 6]. However, it is still unclear which factors drive the attention of citizens towards social media messages coming from police information sources. There are various parameters that can influence engagement on Twitter, such as the characteristics of the content, writing style, time of posting, network position, etc. [1, 8, 9, 10, 11, 12]. Analysing these parameters can help identifying actions and recommendations that could increase public's engagement.

In this paper we present a pilot study developed in collaboration with the Dorset Police, UK. This organisation is moving towards a more engaging style of social media usage and it is interested in scientifically identifying best practices for engaging the public on Twitter. For the purpose of this study we have collected 3,200 posts from @*dorsetpolice* Twitter account and we have investigated the key characteristics of those messages attracting the citizen's attention. To investigate engagement towards these messages we propose a combination of Machine Learning (ML) and semantic analysis techniques. Using ML analysis techniques we aim to identify the key language and time features of those messages. In addition, a semantic content analysis is used to investigate the key topics (concepts and entities) associated with engagement.

Our results show that writing longer tweets, with positive sentiment, and sending them out before 4pm, was found to increase the probability of attracting attention. Additionally, citizens are more interested about tweets mentioning places and related with topics such as weather conditions, roads and infrastructures. Note that, this study is not meant to be a representative of all forces, but rather a focused study on @dorsetpolice. Future work will include the analysis of other police forces [4].

The rest of the paper is organised as follows. Section 2 provides an overview of the related work in the area of policing engagement in social media. Section 3 describes the dataset used in this work and the results of the conducted engagement analyses. Conclusions are reported in section 4.

2 Related Work

Previous studies have investigated police adoption in social media by measuring the growth in the number of followers of Twitter police accounts. Crump, J. [2], for example, obtained a positive correlation between the number of followers and the length that an account had been active. This study also investigated the topics of tweets posted by police accounts and extracted four main categories for those topics: patrol (reports from police patrolling), information (police requesting information from the public), partners (messages associated with emergency services or local authorities) and other (messages that did not relate to any of the above categories).

Heverin, H. investigated the use of Twitter by police departments from large U.S. cities (cities with populations greater than 300,000). This study found that the primary use of Twitter by city police departments is informing about crime or incident related information (45.3 % of tweets). Other uses of Twitter included sharing department, event, suspect, prevention, and traffic information. This study highlighted that; overall, city police departments do not use Twitter to converse directly with members of the public.

Other works have analysed policing messages in the context of riots [3] and protests [6]. The work of Denef et al. [3] analyses the Twitter communication by the London Metropolitan Police (MET) and the Greater Manchester Police (GMP) during the London riots in August 2011. The study concluded that, while MET followed an instrumental approach in their communication, in which the police aimed to remain in a controlled position and keep a distance to the general public, GMP developed an expressive approach, in which the police actively decreased the distance to the citizens.

Earl et al. [6] analysed the engagement of citizens (protesters) during the 2009 G20 meetings held in Pittsburgh. This study concluded that, during this event, Twitter was used by the citizens to share information that was formerly monopolized by the police, such as the location of the police or their actions; creating new dynamics in protester and police interactions.

While all these works focus on understanding the different approaches of police communication, and the different topic categories of such communication, none of these works investigate the engagement dynamics of the citizens towards social media policing content. Understanding what are they features of those messages that attract the citizen's attention (How are they written? When are they posted? Which topics they talk about?) may help police forces to enhance the impact that they have on their communities.

3 Engagement Analysis

In this section we present our engagement analysis study. For the purpose of this study we have collected the latest 3,200 posts from the @dorsetpolice Twitter account, published between 2011-12-23 and 2014-06-12. This account has around 14K followers, and over 3.3K tweets in the form of announcements, appeals, crime reports, etc. From the collected 3,200 posts (note that this limit is established by the Twitter API), 733 are not originally written by @dorsetpolice, but are messages retweeted from other sources. Also 74 of the collected posts are not initialisations but replies to other tweets.

To analyse these data we use a two-phase approach. In the first part we apply a machine learning analysis method [1] to identify the key linguistic and time characteristics of those posts attracting attention. In the second part we conduct a semantic analysis to extract the key topics (concepts and entities) of the policing messages. We combine machine learning with semantic technologies to better understand, not only how and when messages should be written to attract attention, but also which topics users are more likely to engage with.

3.1 Expressing Engagement in Twitter

In the Twitter platform, retweeting, favouring and replying are actions that require an explicit interaction from a user towards another one. These actions have been repeatedly considered in the literature of social media as engagement indicators [8, 9, 10, 11, 12]. In total, the posts generated by the @dorsetpolice Twitter account received 30,726 retweets. To provide an overview, the following table shows the top 10 retweeted posts in our collected dataset.

Table 1: Top 10 retweeted posts. Note that mentions and links have been anonymized

Post	Date	Ret
Regarding tweets to *@user1* - We are aware of the issue and we are actively looking into it.	2012-07-30 22:47:19	6672
Regarding tweets to *@user1* - 17-year-old man arrested this morning at	2012-07-31	5069

a guest house in the Weymouth area. Enquiries continue.	07:51:26	
RT *@user2*: URGENT ALERT (please RT) Mass ransomware spamming event targeting UK computer users. More... *URL_1*	2013-11-18 09:39:44	1434
RT *@user3*: Today is #WorldMentalHealthDay RT if you agree: We need support and respect. We won't give up. *URL_2*	2013-10-10 09:54:56	853
RT *@user4*: Please RT: Stay away from the shoreline this evening/tomorrow. Coastal paths could be dangerous. Risk of being swept out to …	2014-01-02 13:48:04	392
RT *@user5*: Have you seen missing person Richard Brockbank from Newbury? *URL_3* *@user6* #findbrocky *URL_4*	2014-05-21 16:46:58	235
RT *@user7*: Severe weather warnings have been issued for the next five days. More info at *URL_6, URL_7*	2014-02-04 16:32:23	217
Wanted Poole man Dean Goodwin has been arrested by armed police in Poole and is in police custody	2012-11-27 18:05:15	177
Someone must recognise suspect from #Bournemouth robbery. Call 101 if you do. Please RT. #CCTV *URL_8*	2014-05-07 22:51:59	159
RT @missingpeople: Zara went missing from Wimbourne, Dorset last month. Please #jointhesearch RT and help us find her *URL_9*	2013-06-05 16:21:09	136

As we can see in Table 1, the top two posts talk about the detention of a criminal. The remaining posts focus on a variety of issues, such as sea and weather warnings as well as the tasks of searching for lost people or suspects.

Note that when users retweet they spread the message to their followers (as opposed to favouring or replying) leading to a potential stronger involvement and engagement. In this work we consider retweets as indicator of engagement for the rest of our analysis. Tweets that have been retweeted at least once by the citizens are considered *seed-posts*. Those tweets that have not been retweeted (i.e., have not obtained any direct engagement from the citizens) are considered *non-seed posts*. Table 2 summarises the dataset, and shows the number of seeds vs. non seed posts. As we can see from the table, over the course of nearly 3 years, from 2011-12-23 till 2014-06-12, 86% of the tweets received at least one retweet (*seed posts*).

Table 2: Dataset description (number of seeds vs. non seed posts)

Dataset	Time Spam	Num posts	Seed posts	Non seed posts
Twitter	2011-12-23 2014-06-12	3,200	2,770	430

The next two sections present the analysis of engagement dynamics performed over this dataset. The first part consists on a ML analysis, which aims to detect the linguistic and time patterns of seed vs. non-seed posts. The second part performs a semantic analysis to identify the key topics of seeds vs. non-seed posts.

3.2 Machine Learning Analysis

To identify the key characteristics of those posts generating attention we follow our previous approach [1]. This approach characterises posts by analysing how they are written and when they are published. Our goal is to identify, by using a set of features, the main characteristics of those posts that generate higher levels of engagement. The features considered for this analysis are listed below:

- *Post length*: Number of terms in the post.
- *Complexity*: Cumulative entropy of terms within the posts to gauge the concentration of language and its dispersion across different terms. Let n be the number of unique terms within the post p and fi the frequency of the term t within p. Therefore, complexity is given by:

$$complexity(p) = \frac{1}{n}\sum_{i=1}^{n} f_i(long_n - \log f_i)$$

- *Readability*: This feature gauges how hard the post is to parse by humans. To measure readability we use the Gunning Fox Index[1] using the average sentence length (ASL) and the percentage of complex words (PCW).

$$0.4 * (ASL + PCW)$$

- *Referral Count*: number of hyperlinks (URLS) present in the posts.
- *Informativeness*: The novelty of the post's terms with respect to the other posts. We derive this measure using Term Frequency-Inverse Document Frequency (TF-IDF):

$$\sum_{t \in p} tf_{t,p} \times idf_t$$

- *Polarity*: Average polarity (sentiment) of the post. We are computing sentiment by using SentiStrength,[2] a state of the art method for analysing sentiment in social media data.
- *Mentions*: Number of mentions (references to other users) within the tweets.
- *Time of the day*: Time of the day in which the tweet has been posted.

To extract the key characteristics of those posts generating attention we firstly identify the characteristics of those tweets that are followed by an engagement action (*seed posts*), and we then identify the characteristics of those seed posts that are followed by a high level of engagement (*high number of retweets*).

To perform the first task we train different ML classifiers and select the one that provides a better classification of seed posts, in this case the J48 classifier tree. Once the optimal classifier has been selected, features are removed (one at a time) from the classifier and a drop in performance is measured. Those features that generate a higher performance drop are considered the most discriminative ones, i.e., those ones that better distinguish the seed posts (those generating engagement) vs. the non-seed posts. For more details of the complete analysis process see [1].

Figure 1 shows the result of this analysis. More particularly, the top 4 discriminative features that help distinguishing seed vs. non-seed posts are: post length, complexity, polarity and mentions. Posts that generate some level of engagement are generally longer, present a higher level of complexity (i.e., the post contains many terms which are not repeated often), present slightly more positive than negative sentiment and mention at least one user within the tweet.

[1] http://en.wikipedia.org/wiki/Gunning_fog_index
[2] http://sentistrength.wlv.ac.uk/

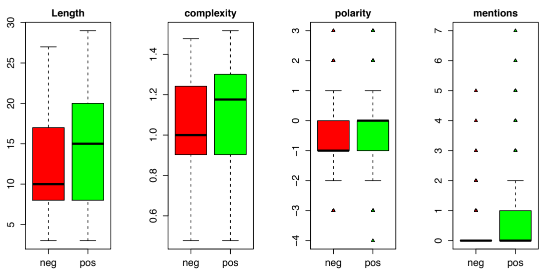

Figure 1: Features with higher influence on engagement levels

Once we have identified the key characteristics of seed posts, our goal is to determine which are the characteristics of those seed posts that generate higher attention levels. To obtain this information we create a linear regression model where the different features listed above are used to approximate the number of engagement interactions that a tweet is receiving. Significant coefficients ($p<0.5$) are associated with complexity, mentions and time in the day. More specifically, those tweets generating higher levels of attention contain many terms that are not repeated often, mention several users in the tweet, and are posted between 8:00 a.m and 16:00 p.m. As Dorset Police indicated, for the moment, there are no dedicated resources for actively tweeting, monitoring or responding to comments outside that time range.

3.3 Semantic Analysis

Understanding the content of the posts, and in particular the key topics of interest for the users, is important to understand engagement. For this purpose we have semantically annotated the tweets of our dataset by using TextRazor.[3] This annotator provides us with the entities from all seed and non-seed posts in our dataset, thereby returning a mapping between each post and a list of DBPedia URIs. We can then identify the concepts that are referred to within a post by looking up each entity's rdf:type in the DBPedia ontology and recording these concepts in a list for each post.

Table 3: Top entities/concepts for seeds vs. non-seed posts

Top Entity [Types] Seed Posts	**Top Entity [Types] NonSeed Posts**
Dorset [Place, PopulatedPlace]	Bournemouth [Place, PopulatedPlace]
Bournemouth [Place, PopulatedPlace]	Weymouth,_Dorset [Place, PopulatedPlace]
England [Place, Country, PopulatedPlace]	Dorset [Place, PopulatedPlace]
Flood	Burglary [Crime]
Weather	Dorset_Police [LawEnforcementAgency]
Weymouth,_Dorset [Place, PopulatedPlace]	Closed-circuit_television
Poole [Place, PopulatedPlace]	Poole [Place, PopulatedPlace]
Snow	Twitter [Organisation, Company]
A31_road [Place, Road]	Bridport [Place, PopulatedPlace]
Collision	Driving_under_the_influence
South_West_England [Place, PopulatedPlace]	Assault [Crime]

[3] https://www.textrazor.com/

Dorchester,_Dorset	[Place, PopulatedPlace	999_(emergency_telephone_number)	
Volvo_XC90	[Automobile]	Traffic	
Severe_weather	[WeatherHazards, Danger]	Robbery	[Crime]
A35_road	[Place, Road]	Property_damage	[Crime]

Table 3 presents the top entities/concepts for the seed and non-seed posts respectively (top entities are the most frequent ones within our dataset). Note that only the URL label has been selected for better visualisation. However, each of those entity labels corresponds to a specific Wikipedia page, e.g. (http://en.wikipedia.org/wiki/Anti-social_behaviour). Also note that not all the entities identified by TextRazor have associated an rdf:type concept in the DBPedia ontology.

Locations, such as Dorset, Bournemouth, Poole or Weymouth are constant across the two groups of posts. However, seed posts include less focalised locations, such as England and South West England. Additionally, seed posts include entities related with weather (snow, severe weather, flood) as well as road an infrastructures (A31 road, A35 road, etc.). Non seed posts, on the other hand, talk about crimes such as burglary, assault or driving under the influence of alcohol.

As we can see from this first overview, semantic entities help us to understand those topics of interests for the citizens, and to differentiate some of the key themes attracting their attention (e.g., road problems or weather conditions). A further analysis should be performed to investigate deeper which combinations of entities spike higher attention levels, in which context they appear (semantic relations with other tweets), and how they differ from the information explicitly provided by hashtags. These are part of our future line of work.

4 Discussions and Conclusions

This paper presents an analysis of policing engagement via social media. The aim of our work is to understand what are the characteristics of the content posted by police forces that attracts higher attention levels. By understanding these characteristics we could provide guidelines to the police forces of when and how they should write their posts; so that police messages reach to larger audiences and increase engagement within the communities.

To analyse this content we propose an approach that combines ML techniques with semantic technologies. While ML techniques help us to understand the more discriminative language and time features of those posts generating attention, semantic technologies help us to better understand and categorise the topics emerging from the content. Our analyses show that, writing longer tweets, with positive sentiment, and sending them out before 4pm, was found to increase the probability of attracting attention. Additionally, tweets about weather, roads and infrastructures, mentioning locations are also likely to attract attention.

It is important to highlight that this is a preliminary study and therefore have several limitations. First of all, only one social media platform (Twitter) has been considered for this study. Other social media platforms, such as Facebook, or even news media articles, should be taken into account to have a better understanding of the citizens' engagement towards social media policing content. Secondly, only one police Twitter account has been selected for the analysis performed in this work. Engagement dynamics may vary across the accounts of different police institutions [4]. Finally, only retweets have been considered as engagement indicator. Other indicators, in particular replies, should be also considered.

Additionally to expanding the number of platforms, accounts, and engagement indicators, our future work includes a deeper exploration of how semantics can be used to understand policing content. In particular we aim to explore the relations among tweets via the semantic entities and concepts they share. Our final goal is to be able to analyse conceptual evolution of the posts over time periods.

Acknowledgments. Thanks to all @dorsetpolice for their contribution to this work

References

1. Rowe, Matthew; Angeletou, Sofia and Alani, Harith (2011). Anticipating discussion activity on community forums. In: Third IEEE International Conference on Social Computing (SocialCom2011), 9-11 October 2011, Boston, MA, USA, pp. 315–322.
2. Crump, Jeremy. "What are the police doing on Twitter? Social media, the police and the public." Policy & Internet 3.4 (2011): 1-27
3. Denef, Sebastian, Petra S. Bayerl, and Nico A. Kaptein. "Social media and the police: tweeting practices of british police forces during the August 2011 riots." Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, 2013.
4. UK Police Twitter Accounts: https://twitter.com/nickkeane/lists/uk-police-force-twitters
5. NPIA. 2010. Engage: Digital and Social Media for the Police Service. London: National Policing Improvement Agency
6. Earl, Jennifer, et al. "This protest will be tweeted: Twitter and protest policing during the Pittsburgh G20." Information, Communication & Society 16.4 (2013): 459-478.
7. Bayerk P.S. et al. Who wants police in social media. 2014. In proceedings of the European Conference of Social Media, Brighton, UK.
8. Meeyoung Cha, Hamed Haddadi, Fabr ́ıcio Benevenuto, and Krishna P. Gummadi. Measuring user influence in twitter: The million follower fallacy. In Proc. 4th Int. AAAI Conf. on Weblogs and Social Media (ICWSM), Washington, DC, 2010.
9. Vicen ̧c Gomez, Andreas Kaltenbrunner, and Vicente Lo ́pez. Statistical analysis of the social network and discussion threads in slashdot. In WWW '08: Proceeding of the 17th international conference on World Wide Web, pages 645–654, New York, NY, USA, 2008. ACM.
10. Nasir Naveed, Thomas Gottron, Jerome Kunegis, and Arifah Che Alhadi. Bad news travel fast: A content-based analysis of interestingness on twitter. In Proc. 3rd Int. Conf. on Web Science, 2011, Bon, Germany, 2011.
11. Daniel Sousa, Luis Sarmento, and Eduarda Mendes Rodrigues. Characterization of the twitter @replies network: are user ties social or topical? In Proceedings of the 2nd international workshop on Search and Mining User-generated Contents (SMUC), Toronto, Canada, 2010.
12. Bongwon Suh, Lichan Hong, Peter Pirolli, and Ed H. Chi. Want to be retweeted? Large scale analytics on factors impacting retweet in Twitter network. In Proc IEEE Second Int Conf on Social Computing (SocialCom), 2010.