Psychological Effects of Urban Crime Gleaned from Social Media

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Abstract

Exposure to frequent crime incidents has been found to have a negative bearing on the well-being of city residents, even if they are not themselves a direct victim. We pursue the research question of whether naturalistic data shared on Twitter may provide a "lens" to understand changes in psychological attributes of urban communities (1) immediately following crime incidents, as well as (2) due to long-term exposure to crime. We analyze half a million Twitter posts from the City of Atlanta in 2014, where the rate of violent crime is three times of the national average. In a first study, we develop a statistical method to detect changes in social media psychological attributes in the immediate aftermath of a crime event. Second, we develop a regression model that uses historical (yearlong) crime to predict Twitter negative emotion, anxiety, anger, and sadness. We do not find significant changes in social media affect immediately following crime in Atlanta. However we do observe significant ability of historical crime to account for heightened negative emotion and anger in the future. Our findings have implications in gauging the utility of social media to infer longitudinal and population-scale patterns of urban well-being.

Introduction

Frequent incidents of crime, ranging from violent crimes to petty theft pervade several American cities. The impact of crime on general well-being is profound (Skogan 1981). Those most directly impacted are the victims of crime. However fear of crime impacts a much larger population, influencing their mundane personal decisions, such as a late night stroll in a particular neighborhood, to important life choices, like purchase of real estate. While statistics from the Federal Bureau of Investigation[1] and the US Census Bureau[2] report that city crimes in the US have been on the decline since 1991, some of the biggest metropolitan cities are still disproportionately victimized by a variety of crime events on a daily basis.

Adoption of social media and social networking sites such as Twitter and Facebook has been on the rise, and a body of research has emerged over the past few years which has identified these platforms to reflect individual and population's psychological states and milieu (De Choudhury et al, 2014; Coppersmith et al. 2014). In this paper, we present an investigation of the psychological effects of short and long-term urban crime exposure as gleaned from social media.

We specifically focus on Atlanta, Georgia; the City of Atlanta has a population close to half a million. Atlanta experiences a violent crime rate of 13 per 1,000 residents – this rate is only 3.7 for the entire US. Further, Forbes[3] recently ranked Atlanta to be the sixth most dangerous city in the US among those with more than 200,000 residents. This motivates our choice of the city for studying the relationship between crime and social media affect.

The main contributions of this paper are as follows:

(1) We present a novel statistical method to investigate changes in social media psychological attributes *in the immediate aftermath* of a crime incident.

(2) We present a second study in which we determine relationships between social media psychological attributes and *historical* crime in a given geographic area.

Our findings indicate that in the context of the City of Atlanta, crime events, in their immediate aftermath (week-long period), do not lead to significant changes in negative emotion, anger, anxiety, and sadness manifested in tweets from the same geographic area. However, we *do* observe a significant link between high historical, long-term (year-long period) crime rates and increased negative emotion and anger measured from Twitter. Through this study, we shed light on the role and limitations of social media in gauging well-being in urban areas affected by crime.

Background and Motivation

A rich body of work in the social sciences, especially urban sociology and criminology, has examined the relationship between crime in urban environments and general well-being of residents (Ross et al, 2000; Pacione, 2003). Skogan (1981) found that fear of crime may stimulate and accelerate neighborhood decline. Increasing fear of crime

[1] http://www.fbi.gov/about-us/cjis/ucr/ucr
[2] https://www.census.gov/compendia/databooks/2010/www/crime.html

[3] http://www.forbes.com/sites/danielfisher/2012/10/18/detroit-tops-the-2012-list-of-americas-most-dangerous-cities/

may further cause individuals to withdraw physically and psychologically from community life (Covington & Taylor, 1991). It can also lead to psychological distress, depression and feeling of powerlessness (Ross et al, 2000).

The above findings serve as a motivation for our study. We observe that the social science body of work in this space has mostly used survey and other self-reported data alongside official statistics on crime (e.g., the Census). Through this paper, we attempt to examine whether naturalistic data shared through social media and spanning large populations might address the generalizability and large-scale validity of the findings in this literature.

The statistics literature also contains several investigations around the predictability of urban crimes using spatio-temporal methods, also known as "hot spot methods" (Chainey et al, 2008), regression (Wang et al, 2012), point process models (Wang & Brown, 2011).

Finally, although limited, there has been some prior work examining the link between urban crime and social media. This includes work on using Twitter to predict crime in Charlottesville, VA (Wang et al, 2012) and Chicago (Gerber 2014). Kim, Cha, and Sandholm (2014) built a system that suggested safe routes in Chicago utilizing Twitter data. They found that Twitter sentiment showed correlation to crime in Chicago. Potential link between persistent violence exposure and social media affect was examined by De Choudhury et al. (2014) in the context of the Mexican Drug War. Other research investigated psychological reactions as manifested in Twitter in the aftermath of major disasters, particularly the Boston bombings (Glasgow et al 2014). Though not related to crime directly, Coppersmith et al. (2014) leveraged Twitter data to predict PTSD in populations in or around military bases. The above body of work indicates that social media can be a viable "lens" that can be utilized to detect psychological attributes of dwellers of regions of known high crime.

Data

We utilized Twitter's streaming API to collect posts geotagged to be originating from the city of Atlanta. In this paper, we use Twitter posts that were collected by this process between October 10, 2014 and December 17, 2014. Our dataset consisted of 518,928 posts from 37,746 users.

We also collected crime statistics (*http://www.atlantapd.org/crimedatadownloads.aspx*) reported by the Police Department of Atlanta spanning two time periods: (1) historical crime in 2014 between Jan 1, 2014 and Oct 9, 2014; and (2) current crime incidents over the same time period as the tweet data, i.e., Oct 10, 2014 to Dec 17, 2014. The crime events are categorized into various types by the PD. For the purposes of this paper, we make use of the four most widely prevalent types of crime in Atlanta – homicide, robbery, aggravated assault, burglary.

Finally, we also collected information about United States Census Bureau reported 2010 Census block groups in Atlanta (*factfinder.census.gov/*). Note that, we deemed the "block group" to be a suitable unit here – it is the smallest geographical unit used by the Census for which the bureau publishes sample data.

Psychological Measures of Tweets: Then we make use of the popular and extensively validated psycholinguistic lexicon LIWC (*http://www.liwc.net*) in order to derive psychological measures in tweets. Since we are interested in examining the impact of crime, we specifically focus on the following LIWC categories: negative emotion (NA), anxiety, anger, and sadness. LIWC is extensively validated in the literature, and prior work has used these categories to successfully characterize Twitter affect and emotion (De Choudhury et al. 2014). Specifically, for each tweet in our dataset, we compute the following four fractions corresponding to the four LIWC categories – ratio of the number of words in the tweet that are present in a LIWC category, to the number of non-stopwords in the tweet.

Results on Short-term Impact of Crime

We first considered analysis of short-term effects of crime events on social media derived psychological attributes of individuals in different block groups. Corresponding to each crime event, we utilized tweets from the census block group in which the incident was reported, and constructed two sets – first corresponding to tweets in seven-day periods *before* the reporting of the crime, and the second corresponding to seven-day periods *after* the crime event. This procedure was conducted for each crime event in the time period overlapping with the tweets – Oct 10-Dec 17, 2014.

Using these tweet collections, we then computed changes in frequency of LIWC NA, anger, anxiety, and sadness in tweets between the "before" and "after" periods. To test the significance of these changes, we performed a "permutation test", permuting the list of timestamps of the crime events; fifty permutations were performed. In each permutation, the marginal distributions over block groups and times are identical, but the link between these variables is broken, so that the tweet collection windows do not correspond to the time and place of actual crime events. For each LIWC category, we used the permutations to estimate the null hypothesis distribution over the difference in means, enabling the computation of a z-statistic. We also computed the L1 distance (Lee, 1999) between the word distributions corresponding to a LIWC category in the "before" and "after" periods, and again compared against distribution of L1 distances over permutations of the original data. In both cases, we found *no* significant effects for any of the four crime types. Summarily, this suggests that the short-term impact of crime in different block groups is not detectable in our social media sample.

Measuring Long-term Impact of Crime

In our next study, we examined whether there is a relationship between exposure to crime events over a long period of time and social media measured LIWC attributes. Here, we measure the long-term impact of crime at the block group level: It is likely that the majority of crime are areaspecific, and therefore likely to impact more individuals who are geographically proximate to the crime location.

(1) Hence we first categorized all our tweets into different Census block groups using the geolocation information in tweets. Then we computed a mean measure of NA, anger, anxiety, sadness over all tweets in each block group.

(2) Next, for each block group, we calculated the historical crime statistics, using the crime data we collected between Jan 1-Oct 9, 2014. We divided the number of crimes by the population of the block group provided by Census in order to generate the crime per capita for the block group for each crime category.

(3) Finally, we also compiled a set of demographic and socio-economic status (SES) variables per block group, as given by Census data. Our motivation for computing the demographic and SES variables was that it is known these variables can differ widely across different census block groups. We used the following variables – proportion of males in population, median age, median income, proportion of population who are high school graduates, and proportion of population who have a bachelor's degree.

Following this, we framed a regression task, where our **dependent variable** was the mean LIWC NA, anger, anxiety, or sadness per block group, and **independent variables** were different types of crimes that happened before the tweet time period i.e., Jan 1-Oct 9, 2014, and the demographic and SES variables in the same block group. Specifically we used a two phase linear regression – first we built a "baseline model" for each LIWC category where only the demographics and SES variables were used. As a next step, we build a "crime model" where we used both demographics and SES and crime data as independent variables. Note that, for analysis we only included those block groups entirely within the Atlanta jurisdiction map (*N*=235). Block groups were excluded if they had no census population or no population of age eligible for one or more of SES independent variables utilized in the analysis.

Results on Long-term Impact of Crime

NA-Crime Model. From Table 1, we observe that adding crime related variables to the baseline model (that uses only demographics and SES variables) results in improvement of model fit for NA. The negative of the log likelihood of the crime model decreases (Likelihood ratio=20) and the adjusted R^2 reduces by 29%. Based on a chi-square test ($\chi 2$ (N=235)=10, p<.0001) we find this difference to be significant over the baseline model. We find all crime types, except robbery to have positive *t*-statistic values – this indicates that increase in homicide, aggravated assault, larceny and burglary are associated with heightened NA in twitter posts for the block groups we examine.

Variables	Baseline *t*-stat	Crime *t*-stat
(Intercept)	7.988 ***	8.676 ***
male ratio	0.959	0.077
median age	-0.966	-1.350 **
income	-3.352 ***	-1.718 ***
prop high school	-0.878	-0.429
prop bachelors	-2.475 **	-1.484 *
prop under poverty	0.145	1.766 **
homicides		1.501 **
robbery		-1.713 ***
assault		2.372 ***
larceny		1.569 *
burglary		0.297
df	228	223
Log likelihood	-730.9	-740.9
Likelihood ratio wrt baseline		20
p	4.81E-22	4.02E-23
adj. R^2	0.322	0.416
* p < 0.05 ** p < 0.01 *** p < 0.001		

Table 1. Linear regression model results with LIWC Negative emotion in Census block groups as the dependent variable. Baseline model includes only demographic and SES variables. Crime model includes historical crime data per capita along with demographic and SES as the independent variables.

Anger-Crime Model. Next we observe that addition of crime variables in predicting anger also results in an improved model fit, compared to the baseline model (Table 2). The negative of the log likelihood decreases (Likelihood ratio=20.6) here and the adjusted R^2 decreases by 8.4%. A chi-square test ($\chi 2$ (N=235)=10.3, p<.0001) shows the improvement in model fit over baseline to be significant. The strongest crime variables here are again robbery and assault, followed by larceny and homicide.

Variables	Baseline *t*-stat	Crime *t*-stat
(Intercept)	7.663 ***	5.854 ***
male ratio	1.136	0.328
median age	-1.584 **	-1.992 ***
prop bachelors	-3.554 ***	-1.844 **
prop under poverty	1.388 **	1.531 **
homicides		0.688 *
robbery		-2.009 ***
assault		3.395 ***
larceny		1.441 **
df	228	223
Log likelihood	-860.4	-870.7
Likelihood ratio wrt baseline		20.6
p	4.75E-25	1.06E-25
adj. R^2	0.41	0.448
* p < 0.05 ** p < 0.01 *** p < 0.001		

Table 2. Linear regression model results with LIWC *Anger* in Census block groups as the dependent variable. Only significant variables are shown.

Anxiety-Crime Model. Our third model examines the predictability of LIWC anxiety words in tweets using crime variables (Table 3). The performance of this model is relatively worse compared to the previous two models. Here, we still see slight decrease in negative of the log likelihood of the crime model over the baseline (Likelihood ratio=10.4); the adjusted R^2 also shows some reduction (13.5%). A chi-square goodness of fit test however does not yield significance here ($\chi 2$ (N=235)=5.2, p=.13).

Variables	Baseline *t*-stat	Crime *t*-stat

(Intercept)	5.182	***	4.121	***
median age	1.838	**	1.693	**
income	-2.053	**	-2.552	***
prop under poverty	1.276	*	1.793	**
robbery			-1.907	***
df	228		223	
Log likelihood	-1028.5		-1033.7	
Likelihood ratio wrt baseline			10.4	
p	1.24E-07		2.08E-07	
adj. R^2	0.148		0.168	
* p < 0.05 ** p < 0.01 *** p < 0.001				

Table 3. Stepwise regression model results with LIWC *Anxiety* in Census block groups as the dependent variable. Only significant variables are shown.

We do not include detailed model results for sadness for space limitations. The performance of this model is the poorest among the four in terms of model fit (adjusted R^2=.044). We also find only marginal improvement in the crime model over the baseline model that uses only demographic and SES variables – a chi-square goodness of fit test does not show significance ($\chi2$ (N=235)=3.7, p=.21).

Together, the four models indicate that while there is variability in *what* psychological attributes in tweets may be predicted using crime data, for NA and anger we see notable ability of historical crime to explain variance. Among the different crime variables, robbery shows significance consistently for the first three models – NA, anger, anxiety. Aggravated assault is highly significant for NA and anger. Surprisingly, we found homicide to be significant only marginally for our models; it is significant only for NA, anger, and sadness. To summarize, the regression models indicate that historical incidence of homicide, robbery, larceny, and burglary are important predictors of the psychological content of tweets in a future period.

Discussion and Conclusion

In our first study, our results did not indicate the presence of any short-term impact of crime on social media derived psychological attributes. Better user filtering may help to focus on user accounts which are particularly likely to be affected by crime events. We may also wish to focus on a more homogeneous set of neighborhoods, such as residential areas, since likely, both the distribution of crimes and of Twitter content differs substantially in downtown areas. Additionally, through the permutation test we did not account for the presence of cascading effects of crimes, or crimes that impact communities differentially. Gauging how residents of these areas learn about the crime events and their (media) exposure will help us better interpret the findings. In the future, we are also interested in analysis of additional variables that may explain the observed effects.

On the other hand, in the next part of our study corresponding to determining the impact of long-term crime, our results showed that historical incidence of criminal activity is related to social media in the same area at a later time. Perhaps expected, data also showed that demographic characteristics, in particular income and education, have a large effect on the psychological measures derived from Twitter. However, the predictivity of crime variables remained significant even after controlling for SES variables.

Overall the findings of our historical crime study align with those in the literature (Skogan 1981) – we show long-term exposure to crime to be associated with heightened negative emotion and anger. We conjecture that perhaps in a city like Atlanta, crime impacts individuals, however only when it is beyond a certain exposure level. Hence we find that while crime was not correlated with social media affect immediately, it was so when we considered a longer-period of crime incidents. While a causal relationship may not be directly inferred, we hope our findings to shed light on the potential and limitations of using social media as a lens to understand urban well-being longitudinally.

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