# INVESTIGATING CRIME-TO-TWITTER RELATIONSHIPS IN URBAN ENVIRONMENTS - FACILITATING A VIRTUAL NEIGHBORHOOD WATCH

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*Complete Research*

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## Abstract

*Social networks offer vast potential for marketing agencies, as members freely provide private information, for instance on their current situation, opinions, tastes, and feelings. The use of social networks to feed into crime platforms has been acknowledged to build a kind of a virtual neighborhood watch. Current attempts that tried to automatically connect news from social networks with crime platforms have concentrated on documentation of past events, but neglected the opportunity to use Twitter data as a decision support system to detect future crimes. In this work, we attempt to unleash the wisdom of crowds materialized in tweets from Twitter. This requires to look at Tweets that have been sent within a vicinity of each other. Based on the aggregated Tweets traffic we correlate them with crime types. Apparently, crimes such as disturbing the peace or homicide exhibit different Tweet patterns before the crime has been committed. We show that these tweet patterns can strengthen the explanation of criminal activity in urban areas. On top of that, we go beyond pure explanatory approaches and use predictive analytics to provide evidence that Twitter data can improve the prediction of crimes.*

*Keywords: Decision Support, Predictive Analytics, Social Media, Big Data.*

## 1 Introduction

After the attack at the Boston Marathon, the police were calling on the public for help to find the terrorists. Authorities encouraged people to report suspicious activities during, before and after the marathon. In addition, officials also asked for photos and videos. As a response, the local police received large amounts of digital data captured on digital cameras, smartphones and other devices within days. Even though not every received piece of information was valuable or correct, the enormous amount of data submitted demonstrates the vast potential that lies in online social collaboration. Effectively, using "the crowd" has worked well to solve crimes (Markowski 2013).

The advent of social media has clearly fueled enforcement agencies calling on the public for help in solving crimes and finding culprits. Twitter and Facebook is often used to report crimes and to respond to calls for witnesses and information. Proofs of concept exist that utilize the mobile mass media for sensing in urban areas (Roitman et al. 2012). Many platforms use this idea of crowdsourcing, i.e. the process of taking work and outsource it to a crowd of workers, for receiving information from the public to assist the police in mapping criminal activities. The use of smartphones with their ability to upload photographs or videos with accurate GPS location is most helpful. Examples for crime watch crowdsourcing platforms are Postacrime.com, Spotcrime.com, or CrimeReports. Ultimately, the information provided by these platforms may not only help the police to catch criminals but also allows for analyzing the data for patterns to establish a digital neighborhood watch program based on social

media. The challenge, however, is to encourage people report crime patterns or suspicious activities. In this paper we address this challenge of crowdsourcing crime by using general Tweets and fusion them with crime data to explore patterns of crime that can be exploited by the police and authorities.

Social networks such as Twitter, Facebook, and Flickr seem to fill the requirements for crowdsourcing predicting and fighting crimes, as the past couple of years have brought an immense increase to the activity in messaging. Twitter, for instance, has attracted the amount of tweets per day from 20,000 in March 2007 to 400 million in March 2013, which is an increase of 20,000 percent within six years (cf. Figure 1). The increased usage of online social services is foremost related to the growing ubiquity of mobile online devices and the increased interest for online interaction at younger ages. By use of their mobile devices for participation in online social interaction, users often provide both temporal and spatial coordinates. Either, spatial information can be inferred from rough location estimation delivered by the social network provider, or it is directly attached to users' posts as exact geographic coordinates. Hence, while navigating through a city, no matter whether they follow their own interest or another obligation, social network users leave their mark on their exact routes and thus blur the distinction between their physical habits and virtual traces.
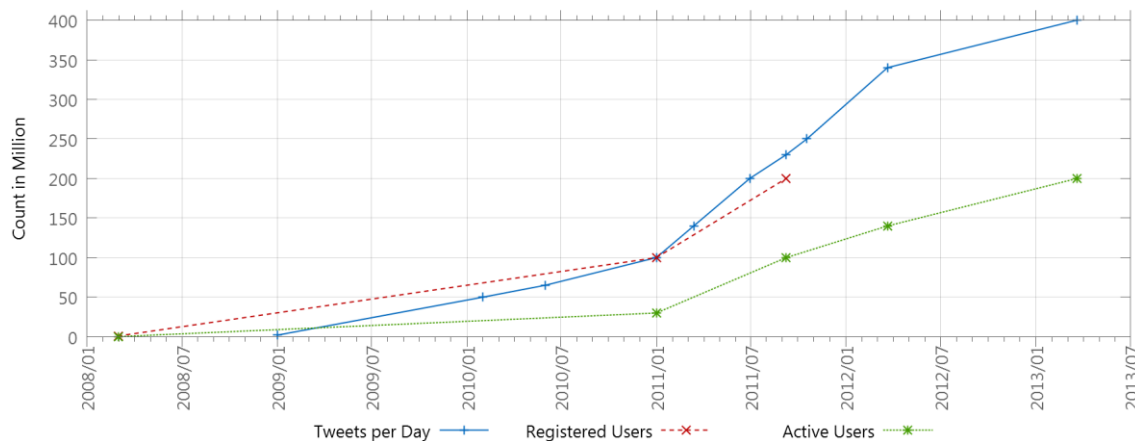


*Figure 1.        Twitter usage statistics in tweets per day, registered users and active users (Source: blog.twitter.com).*

Considering Twitter, information drawn from user-contributed posts actually reflects socially active spots with typically more than 500 million Tweets per day, most of them from urban areas. Instead of analyzing general trends, we move a step ahead by anchoring our Twitter analysis to small areas in fine-grained time periods. This anchoring to precise locations accounts for the fact that environmental conditions in urban areas, such as demographic, cultural or financial aspects, infrastructure, or public facilities, may change from one block to another. Clearly, environmental conditions are hard to indicate and analyze in-depth, but with Twitter posts may serve as a proxy for public activity in certain areas of a city. Areas where many Tweets are posted in close temporal adjacency in a small area, we expect with a certain probability that an event may cause the majority of Tweets. This assumption may in particular apply to crimes, as specific Tweet patterns may predict criminal activities in a certain area. In absence of public activity, for instance criminal intent for car thefts or burglary may be risen, while in presence of many people these crimes are most probably suppressed and other intents are promoted, such as pickpockets, frauds, vandalism, or disturbing the peace, for example.

The exact inhibiting or repressing factors for criminal intent in urban areas are hard to identify and measure. Despite these aspects being unobserved, the effects in both crime rates and Twitter activity are actually detectable. The sole amount of temporally related tweets in a small area can be related to certain crime types in either directions, supporting or suppressing, no matter what the topic or mood of the respective Twitter users were. We aim to find correlation between Twitter activity and crime rates

caused by unobserved fixed or repeating environmental conditions. In a nutshell, the research introduced in this paper addresses the following questions:

- Does mobile online social activity establish an exploitable relationship between tweet patterns and criminal activities?

- Can we infer real-world implications from massive online activity by sole temporal and spatial adjacency?

- Can Twitter data be utilized to not only explain criminal incidents, but to improve prediction of crimes, before they happen?

As a result of this research it is possible to establish a virtual neighborhood watch, which is fed with actual Twitter messages that bear the potential to predict crimes before they have been committed.

The remainder of this paper is structured as follows. The subsequent section delivers an overview of related research, especially in terms of social network data investigation. In Section 3, we present the data model supporting our empirical research. The extracted data delivers indication of correlation and promotes the empirical analysis using regressions, which is addressed in Section 4. The final Section 5 delivers the results and closes with a summary and future applications of this methodology.

## 2 Related Work

Social media networks like Facebook or Twitter no longer are platforms to solely exchange personal information with friends, family, colleagues, or the public, but rather became a source for marketing data craved by many companies worldwide. The networks cover highly valuable and meaningful information on users' dreams and desires, their behavior and characteristics. Since users around the globe are able to post their opinion concerning any topic imaginable, social media provides powerful data streams for various industrial sectors and also attracted attention in modern-day research for years.

For a broad overview Bontcheva and Rout (2012) introduce key research challenges and questions for mining semantics from social media. They provide a survey on applications and methods of semantic technologies. Although, it is very difficult to extract reliable informant from noisy, subjective social content, research shows that sentiment analysis is an appropriate method to generate an added value in various fields (Chamlertwat et al. 2012, Choi and Kim 2013 and Neri et al. 2012).

In detail, Cheong et al. 2012 try to predict upcoming election results using a census correction Twitter model. However, political tweeter data are always provided by politically active users and they assume trustworthy messages. The authors also do not consider geographical or demographical information. Nevertheless, politics is one of the main fields social media are increasingly used to derive opinions and to forecast future elections (Bermingham and Smeaton 2011, Boutet et al. 2012, Boynton et al. 2013, Bravo-Marquez 2012, He et al. 2012, Gayo-Avello 2012). Skoric et al. (2012) found candidate mentions in the 2011 Singapore General Election were predictive of the relative ranking of the votes a party received, but not the correct vote percentages. They also offer perspective on Twitter political analysis being limited to areas with a democratic press, because observations indicated that opposing parties would be overrepresented on social media.

Another very popular field of research in the context of social media analysis is the finance sector. Bollena et al. (2011) analyze Twitter data to determine the user's mood to predict the value of the Dow Jones Industrial Average (DJIA) over time. Therefore, they use the mood tracking tools OpinionFinder and Google-Profile of Mood States to measure and characterize daily feeds and found that the accuracy of DJIA prediction can be improved by including specific moods. In this context Ding et al. (2012) also predict stock market movements on a daily base. In addition, the research of Cho et al. (2013) show that news recommendations on financial stocks of a crowd are always better than those from experts. The

procedure to forecast stock market prices is often based on complex sentiment analysis. Hence, to actually receive an adequate prediction they need to assume valuable market information inside a tweet.

In certain fields of application ex post analyses are insufficient, because many decisions are made within seconds. Therefore, streaming data need to be analyzed in real-time to discover what is happening in the world at any certain moment in time (Bifet et al. 2011). Since real-time systems are very important in specific areas like early warning, Okazaki and Matsuo (2011) propose an event notification system for earthquakes. The authors do not predict earthquake events, but rather inform users based on an integrated semantic technology. In this regard, Twitter is also frequently used in the health care sector and for early warning systems. Earle et al. (2010) use historic geocoded tweets containing the word "earthquake" to develop a Twitter-based earthquake detection system. Their results show limitations due to the small amount of data for a single event. However, similar to the approach introduced in this paper, they use San Francisco as a reference city and they also use time-bounded and geographically tagged messages, but in a different context. In their further research Earle et al. (2011) extend the detection procedure by a short-term-average, long-term-average algorithm to identify possible earthquakes on a global base. They were able to detect 48 globally distributed disasters with only two false triggers. A similar approach is also used to detect epidemic diseases or pandemic influenza outbreaks like the H1N1 flu pandemic (Lampos and Cristianini 2010, Lampos et al. 2010, Quincey and Kostkova 2010).

Thus, Twitter's attributes reflect the online impact of real-world events in an instantaneous fashion. Therefore, the versatility of Twitter's predictive power allows a wave of research ranging from applications to elections, the stock market, and natural disasters. Because of its large customer base and its high usage every day, Twitter is also able to serve as a real world sensor network (Takahashi et al. 2011 and Croitoru et al. 2013). In the research of Alkutkar et al. (2012) they develop a warning system to check whether a specific location is actually dangerous or not. The authors use social networking data and search for key words such as "robberies", or "drugs" to alert users in a high crime rate prone area. Unfortunately, this approach is not able to get along without sentiment analysis. Since crime is an overall societal challenge Wang et al. (2012) present a preliminary investigation of a Twitter-based model to automatically predict crime incidents. In contrast to our approach the authors use semantic analysis to detect crimes, while we investigate crime-to-Twitter relationships without a sentiment measure.

Hence, as implied by the above literature, the predictive power of social media and especially Twitter feeds in various areas has been proven in recent years and additionally has been shown in the research of Kalampokis et al (2013). Thus, social media can be used to generate an added value in many different sectors. However, almost all of the above research approaches use volume or sentiment analysis to predict or to explain different events or circumstances, but mostly without including any other data like fine-grained temporal or spatial information. Moreover, sentiment analysis requires suitable dictionaries, whereby internet-speech of users with lots of abbreviations, typing errors and creative smileys hinders a complete and valid analysis.

In this paper we introduce an approach to explain and predict criminal activity in urban areas by relying on absolute tweet volume. We show that it is possible to investigate crime to twitter relationships only by temporal and spatial adjacency of both, omitting semantic accordance. Once we have shown exploitable patterns, we can even improve on them by including the tweet content in the future. If tweet patterns on the contrary do not give evidence that there is a relationship between them and criminal activities, it would render the use of content analysis highly doubtful, because the identification and the correct understanding of the relevant tweets becomes a serious issue

# 3    Data Preparation

As aforementioned, mobile online social activity, such as posting tweets, is due to its nature strongly influenced by the vicinity of the user's current location. The geographical position of a tweet may implicitly reveal information about the local environment. Locations, where many people are tweeting

in a certain time window most likely contain special features that explain those people's common interest. The same applies to the incidents of crimes, as for crime-types delinquents require a certain environment. For instance, crowded places can establish opportunities for pickpockets, and public areas close to nightclubs and bars can evoke civil violations at night, such as disturbing the peace. Besides the geographical location, the time of day plays an important role for both tweeting behavior and crime rate.

Instead of analyzing the geographical environments in all of their multifarious aspects, we aim to accomplish an indirect relationship between mobile online social activity and crimes only by their adjacency in both time and geographical dimension.

While official data on a crime's place and time is mostly exact, we may encounter uncertainty in social media data. Both required dimensions time and location in most cases transmitted by social network providers, can be uncertain. It is not guaranteed that a message relates to the point in time it was transmitted, because users can send their messages retrospectively or anticipatory. Furthermore, the location can be uncertain, either due to blurring applied by the provider, or because a user has covered quite a distance before transmitting the message. Anyhow, alone by the vast amount of messages being transmitted each hour, we obtain a fine-grained view on the general public activity in urban areas.

In order to analyze interferences and possible inferences between online social activity and crimes, we design a data model capable of delivering required metrics. This enables us to employ an empirical analysis in the subsequent step to assess relationship between these two societal measures, and to finally set up and train a Support-Vector Machine for improved crime prediction. In a first step, we outline the general data characteristics, followed by a formal definition as a preliminary to the empirical analysis.

## 3.1 Data Sources

In this research, we investigate data related to an urban subarea from within the city of San Francisco. The time span covers three full months, from August 15, 2013 to November 14, 2013, resulting in more than 60 thousand geo-tagged Twitter status messages and more than thirteen thousand registered delinquencies. For our analyses, we can only rely on Twitter status messages that provide geographical information, which is around one per cent of all tweets. Given the high activity in Twitter all around the world and especially in urban areas, the small fraction of Tweets coming with geo-tags can serve well as a proxy for general Twitter activity. In order to be able to carry out meaningful analyses and to generate valid results, we choose an area around the Market Street in San Francisco, which delivers a quite high Twitter activity. We cover the chosen area by a $10 \times 10$ lattice of cells with approximately 200 meters edge length each, as indicated in Figure 2. Twitter data were collected using the Twitter API, data on criminal activities stem from crimemapping.com.
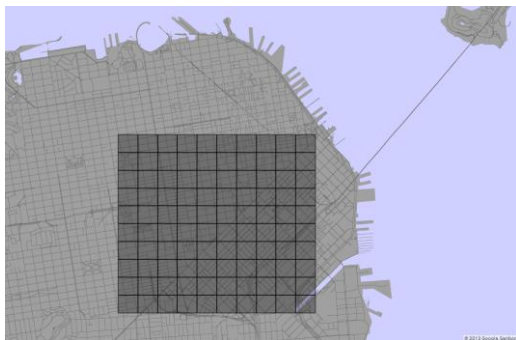


*Figure 2.        Lattice indicating the exact selected area in San Francisco*

The motivation to employ a grid-based approach and to carry out analyses by direct relation between Twitter user behavior and crime observations is manifold. In a general approach, a broad range of societal (cultural, financial, demographical) aspects of the covered area would be required to be analyzed

in depth. We do not search for the exact events that cause crime rates to vary or tweet numbers to increase or decrease but compare the consequences in these two measures directly. We focus on the sole adjacency in the dimensions of time and location for both tweets and crimes and expect the certain societal aspects that may have induced variations in time or location, such as demographic characteristics for instance, to be implicitly covered by the recorded data. The grid approach allows the societal conditions to vary between cells due to the strict separation among them. Thus, the deep analysis of the societal aspects in the selected area can be omitted. Application of this approach even allows the grid to be scaled or shifted, as well as its resolution to be increased or decreased without requiring re-assessment of the covered area's environmental conditions.

Since both Twitter activity and criminal incidents vary depending on hour of day and day of week, panel data observations have to be kept fine-grained, for example on an hourly base, throughout the covered time period. We expect activity shifts to occur not only in the geographical location but rather in the full combinatorial space of time and place. The plots shown in Figure 3 deliver an idea of the aggregated distribution of Tweets and, exemplary chosen, disturbance of peace. It clearly indicates that it is absolutely necessary to divide observations two-dimensionally, as variations in activity occur according to changes in both time and location.
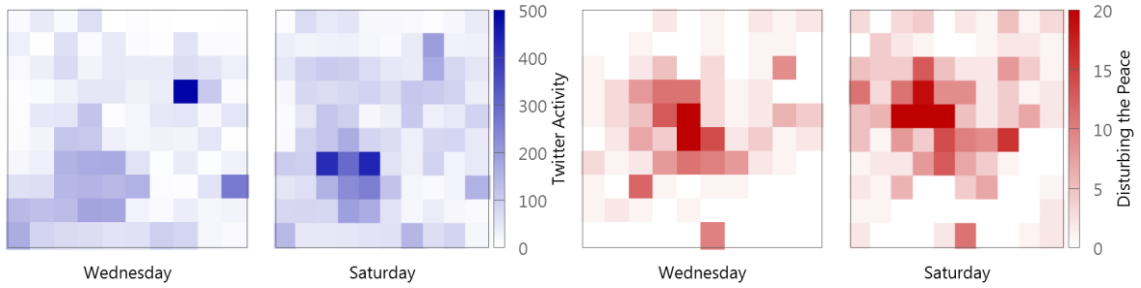


*Figure 3.        Activity in tweets and "disturbing the peace", aggregated over all Wednesdays and Saturdays over the whole observation period.*

The two panels to the left in Figure 3 show the Twitter activity in the selected grid, aggregated over all Wednesdays and Saturdays of the observation period. We can clearly identify differences between these two, indicating a location shift in Twitter activity depending on the day of week. The very same can be observed by comparison of the two panels on the right, which show the density of peace disturbances.

## 3.2    Formal Description and Characteristics

The entire time span observed in this work is split into time steps $t$ of one hour width each. Starting on August 15, 2013 and ending on November 14, 2013, we obtain 2184 time steps in total, as shown in Equation (1.1). Furthermore, all available Twitter status messages are defined as the set $W$, where each single tweet $w \in W$ represents a 3-tuple, defined in Equations (1.2) and (1.3). For each tweet $w$, $\phi_w$ and $\lambda_w$ describe the corresponding latitude and longitude values of its geo-location, respectively. The property $t_w$ represents the time step, which relates to the specific point in time where the message was actually published. Since we are not analyzing the textual content of tweets in the scope of this research, the message itself is omitted.

$$t \in \{0,1,\dots,2183\} \tag{1.1}$$

$$W = \{t_1, t_2, \dots, t_{|W|}\} \tag{1.2}$$

$$w \in W \mapsto (\phi_w, \lambda_w, t_w) \tag{1.3}$$

Similar to the formalization of tweets, we collect all recorded crimes in the set $C$, as outlined in Equation (2.1). Each crime maps to a 4-tuple containing information on the geographical location described by

$\phi_c$, the latitude, and $\lambda_c$, the longitude. Furthermore, the tuple holds the time step $\tau_c$ defining the point in time where the crime happened, as well as $\theta_c$, which relates to the type of the crime. The crimes' properties are defined in Equation (2.2).

$$C = \{c_1, c_2, \dots, c_{|C|}\} \tag{2.1}$$

$$c \in C \mapsto (\phi_c, \lambda_c, t_c, \theta_c) \tag{2.2}$$

The set $\Theta$ contains all types of crimes that are available, as defined in Equation (3). We have collected crime data on 14 different categories. Please refer to Table 1 for the exact denominations.

$$\Theta = \{\theta_1, \theta_2, \dots, \theta_{|\Theta|}\} \tag{3}$$

In preparation for the discrete setup concerning geographical cells, Equation (4.1) defines the grid as a matrix of dimension $X \times Y$, where $Y$ refers to the latitude direction and $X$ represents the longitude direction. According to these grid cells, the sets of Tweets $W$ and crimes $C$ can be further refined, as shown in Equation (4.2) and (4.3). In this context, the tilde $\sim$ describes the geo-spatial affiliation of a tweet or crime to a grid cell. Similarly, the resulting sets $W_{xy}$ and $C_{xy}$ can be filtered to match a certain time slot $t$ as well (Equations (4.4) and (4.5)). The function $h(t)$ allows retrieval of the hour of day the given time slot $t$ refers to using the modulus function, as described in Equation (4.6).

$$G = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1Y} \\ g_{21} & g_{22} & & \\ \vdots & & \ddots & \vdots \\ g_{X1} & & \cdots & g_{XY} \end{bmatrix} \tag{4.1}$$

$$W_{xy} = \{w \in W \,|\, (\phi_w, \lambda_w) \sim g_{xy}\} \tag{4.2}$$

$$C_{xy} = \{c \in C \,|\, (\phi_c, \lambda_c) \sim g_{xy}\} \tag{4.3}$$

$$W_{xy}^t = \{w \in W_{xy} \,|\, t_w = t\} \tag{4.4}$$

$$C_{xy}^t = \{c \in C_{xy} \,|\, t_c = t\} \tag{4.5}$$

$$h(t) = t \bmod 24 \tag{4.6}$$

Distending the grid by observation separation by both hour and crime type results in 3,276,000 observations in total. For the selected area from San Francisco, which spans from north-west $[\phi = 37.795, \lambda = -122.43]$ to south-east $[\phi = 37.77, \lambda = -122.395]$, we have recorded events as outlined in Table 1. Concerning the Twitter status messages, we collected solely those tweets that provided a geo-tag. Since the methodology takes the adjacency in terms of location into account, messages without an accurate geographic location are unusable.

| Observed Event | Obs. Count | Maximum | Mean $\mu \cdot 10^{-3}$ |
|---|---|---|---|
| Twitter Status Message (only geo-tagged) | 60268 | 60 | 275.952 |
| Assault | 1763 | 3 | 8.072 |
| Burglary | 823 | 2 | 3.768 |
| Disturbing the Peace | 2292 | 3 | 10.495 |
| Drugs/Alcohol Violations | 462 | 2 | 2.115 |
| DUI | 101 | 2 | 0.462 |
| Fraud | 500 | 2 | 2.289 |
| Homicide | 2 | 1 | 0.009 |
| Motor Vehicle Theft | 599 | 3 | 2.743 |
| Robbery | 700 | 2 | 3.205 |
| Sex Crimes | 391 | 2 | 1.790 |
| Theft/Larceny | 2035 | 3 | 9.318 |

| | | | |
|---|---|---|---|
| Vandalism | 574 | 2 | 2.628 |
| Vehicle Break-In/Theft | 2360 | 5 | 10.806 |
| Weapons | 539 | 3 | 2.468 |

*Table 1.        Amount of observed occurrences for types of events (Category names from crimemapping.com)*

A total of 3,276,000 data points in regard of the event count provided in Table 1 suggests a sparse data set with 1.1246 per cent of all data points being non-zero. The maximum amount of registered crime acts of respective type in a single cell and a single hour is provided in the third column, the mean value $\mu$ is provided in the last column.
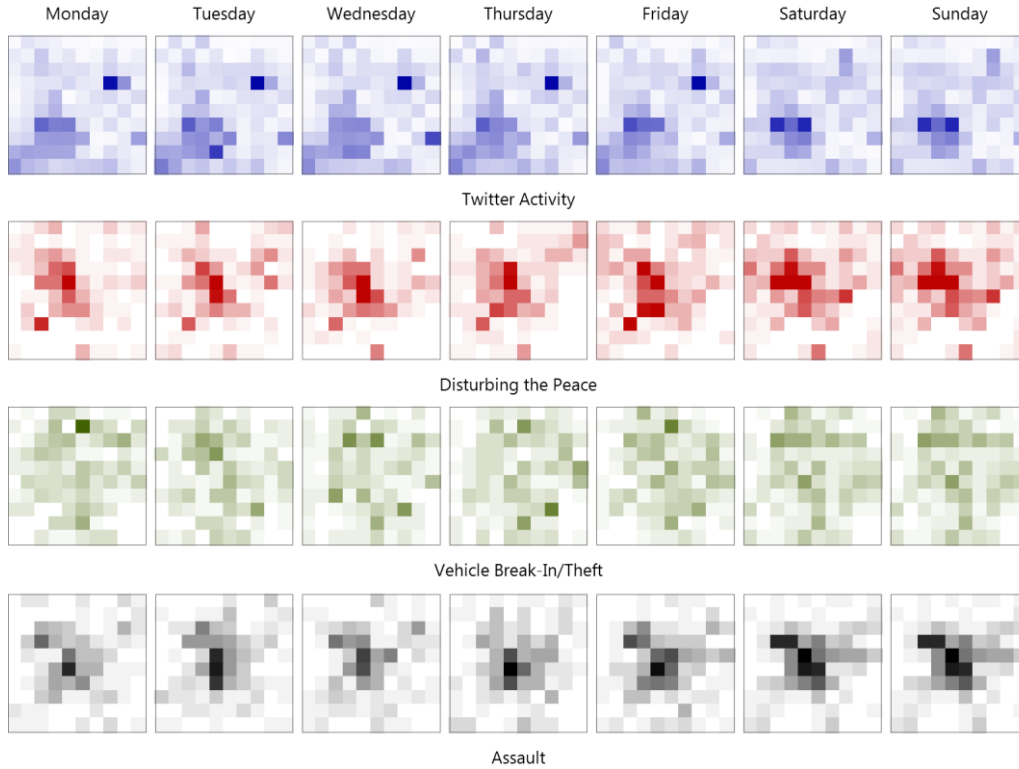


*Figure 4.        Daily aggregates for different observed events.*

Figure 4 indicates the geographical shapes for the four exemplarily selected observed events "Twitter Activity", "Disturbing the Peace", "Vehicle Break-In/Theft", and "Assault". By visually inspecting it, we can clearly indicate an activity shift in all four categories between workdays and weekends. Especially for the Twitter message plots, the considerably dark spot to the top-right of each workday almost completely diminishes when proceeding towards the weekend. Additionally, the wide-spread activity in the lower left corner concentrates in a smaller area. Concerning peace disturbance, we can clearly identify the overall increase towards the weekends, already starting on Fridays. In contrast, the observations of vehicle break-ins or vehicle thefts keep being scattered over the entire area over the whole week. Nevertheless, its pattern for Saturday and Sunday seem to be very similar to each other. The plots for assault-related observations indicate an overall increase and a clear focus on a certain area on weekends, while they seem pattern-less for workdays.

The plotted data visually delivers indicators for repeating pattern in both time and location for Twitter user behavior as well as crime occurrences. However, since the figures only represent aggregated data, it is possible that indicated patterns may refer to completely different times and are not even closely related to each other. Thus, a full regression is required to further investigate possible correlations. As

the subsequent step, the indications will be analyzed in the empirical analysis using a Probit regression in order to find evidence for relations between Twitter activity and crimes. Subsequently, the predictability of criminal activity will be assessed by application of a Support-Vector Machine.

# 4 Empirical Analysis

Generally, we apply two different methods of model building and data analysis – an explanatory approach and a predictive one. According to Shmueli et al. (2011), our aim to understanding and testing data for correlations or causal hypotheses implies an explanatory role, fulfilled by the Poisson regression on our panel data described in subsection 4.1. The second step, described in subsection 4.2, contrastingly aims at improving the predictability of crimes by including Twitter activity as a proxy of social activity and public awareness. We train and test a Support-Vector Machine for quantifying the level of predictability of criminal activity, and thus also cover the role of assessing predictability proposed by Shmueli et al.

## 4.1 Explanatory Analysis

In downtown San Francisco criminal incidents of any kind are, as the data reveals, a relatively rare occurrence, at least from a statistical perspective. Out of 218,300 observations[1] only 11,561 observations report one or more crimes – or 0.053 crimes per tile and hour. Since this rarity suggests that crimes follow a Poisson distribution, we use goodness-of-fit tests using Maximum Likelihood estimation to support this assumption. The results of these tests are reported in Table 2 and strongly confirm that all categories follow a Poisson distribution. This becomes more evident when considering the mean occurrences and variances, which are almost equal for all categories.

A Poisson regression is generally represented by the relationship

$$\mathrm{E}(y \mid \mathrm{x}) = e^{\varphi^T \mathbf{x}} \tag{5}$$

with $y$ as the explained variable, $\mathbf{x}$ the vector of covariates and $\boldsymbol{\varphi}$ the vector of regression coefficients. In our case we aim at explaining the number of crimes belonging to the categories in $\Theta^* \subseteq \Theta$ in a particular cell $g_{xy}$ at time $t$. Hence, the explained variable denotes the amount of crimes in a certain cell at a certain point in time. According to Equation (4.5), we set the explained variable $y$ according to Equation (6).

$$y = \left| \{ C_{xy}^t \mid \theta_c \in \Theta^* \} \right| \tag{6}$$

In this research work we consider for $\Theta^*$ either individual categories (i.e. $|\Theta^*| = 1$) or the sum of crimes over all categories ($\Theta^* = \Theta$). The vector of covariates contains the intercept denoted by "1", the amount of twitter messages at the very cell from the time slot before $\left| W_{xy}^{t-1} \right|$ (cf. Equation (4.4)), and fixed effects term that describe the geographical vicinity $a_{xy}$ and the hour of day $b_{h(t)}$. Thus, $\mathbf{x}$ is set as defined in Equation (7).

$$\mathrm{x} = \begin{bmatrix} 1 \\ \left| W_{xy}^{t-1} \right| \\ a_{xy} \\ b_{h(t)} \end{bmatrix} \tag{7}$$

We use a lagged value for the volume of tweets, such that the regression result can be used to assess the predictability of criminal events based on Twitter activity. The geographical fixed effects term is required, because certain areas are more prone to criminal activity than others. This additionally covers

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[1] 100 grid tiles × (24 hours × 91 days – 1 hour to allow for lagging) = 218,300

unobserved environmental conditions, for instance the local demographic structure, or the local level of education and income, that may have an impact on crime rates in the close surrounding. The second fixed effects term $b_{h(t)}$ is essential, since the occurrence of most criminal incidents follows certain cycles throughout the day. For example, disturbing the peace calls most likely occur during late night hours, while vehicle break-ins and larceny mostly take place during daytime. Naturally, the vector of regression coefficients corresponds to the form of $\boldsymbol{\varphi} = [\varphi_0, \varphi_1, 1, 1]^T$. Plugging in our values, we can summarize the regression model as defined in Equation (8). The expected value of the amount of crimes in a certain cell at a certain time depends on the main intercept $\varphi_0$, the amount of tweets in the same cell in the hour before, weighted by the parameter $\varphi_1$, and the two fixed effects for the certain cell and certain hour of day.

$$\mathrm{E}\left(\ln\left(\left|\{C_{xy}^t|\theta_c \in \Theta^*\}\right|\right) \mid \left|W_{xy}^{t-1}\right|, a_{xy}, b_{h(t)}\right) \tag{8}$$
$$= \varphi_0 \cdot 1 + \varphi_1 \cdot \left|W_{xy}^{t-1}\right| + 1 \cdot a_{xy} + 1 \cdot b_{h(t)}$$

| Type of crime $\theta$ | $\mu$ | $\sigma^2$ | $\Pr\big(y \sim \mathrm{Pois}(\lambda)\big)$ |
|---|---|---|---|
| Crime (general) | 0.0583 | 0.0669 | 1.0000 |
| Assault | 0.0080 | 0.0086 | 1.0000 |
| Burglary | 0.0037 | 0.0039 | 1.0000 |
| Disturbing the Peace | 0.0104 | 0.0115 | 1.0000 |
| Drugs/Alcohol | 0.0021 | 0.0021 | 0.9984 |
| DUI | 0.0005 | 0.0005 | 0.9824 |
| Fraud | 0.0022 | 0.0022 | 1.0000 |
| Motor Vehicle Theft | 0.0026 | 0.0029 | 1.0000 |
| Robbery | 0.0032 | 0.0033 | 1.0000 |
| Sex Crimes | 0.0018 | 0.0018 | 0.9949 |
| Theft/Larceny | 0.0090 | 0.0097 | 1.0000 |
| Vandalism | 0.0025 | 0.0026 | 1.0000 |
| Vehicle Break-In/Theft | 0.0099 | 0.0114 | 1.0000 |
| Weapons | 0.0025 | 0.0026 | 1.0000 |

*Table 2.        Goodness-of-fit tests for Poisson distribution.*

The regression was executed in R using the generalized linear model (GLM) implementation. Fixed effects were calculated using 23 dummy variables for the hours of day and 99 dummy variables for the cells. The estimated influence of the number of tweets in the preceding period for each category is summarized in Table 3. Evidently, a rising number of tweets decreases the expected criminal activity in the subsequent hour in a particular cell. This effect is mainly driven by a decrease in incidents of assaults, theft, and disturbance of the peace. For instance, consider Figure 5 below, which illustrates the varying fixed effects of the grid cells for general criminal activity. Cell $g_{45}$, the darkest red cell in the middle of the grid has an above-average incidence of criminal activity, represented by a fixed effects of $a_{45} = 3.7834$. At noon the fixed effect is $b_{12} = -0.3774$. As the intercept $\phi_0$ is $-4.7296$, the expected number of criminal incidents in that cell in absence of any tweets in the preceding hour would be 0.2662. However, if there were 20 tweets in the preceding hour, this value decreases to 0.1237, i.e. by more than half. Contrastingly, cells with location-related fixed effects $a_{xy}$ close to zero or even negative represent areas that have a much lower incidence of criminal activity (colored green).

Interpreting a crowded street to be safer than an empty one from these findings can be misleading. For certain types of crime this assumption can hold, but the different cell intercepts show that it heavily depends on the corresponding urban district. Twitter as a proxy for social activity can greatly influence the probability for crimes given the cell's fixed effects and the hour of day. Thus, our findings indicate analysis of social media to be a valuable addition to support city and crime management. The resulting advance is beneficial for various target groups that get in contact with safety and security in urban regions, such as tourists, residents, city planning offices, or divisions of local governments.

| Type of crime $\theta$ | Coefficient | Std. Error | z-value |
|---|---|---|---|
| Crime (general) | −0.0383 | 0.0079 | −4.8514 . |
| Assault | −0.0566 | 0.0251 | −2.2526 . |
| Burglary | 0.0021 | 0.0343 | 0.0602 |
| Disturbing the Peace | −0.0578 | 0.0170 | −3.3988 . |
| Drugs/Alcohol | 0.0251 | 0.0324 | 0.7749 |
| DUI | −0.1836 | 0.1129 | −1.6267 |
| Fraud | −0.0649 | 0.0786 | −0.8262 |
| Motor Vehicle Theft | −0.0183 | 0.0481 | −0.3812 |
| Robbery | 0.0183 | 0.0238 | 0.7709 |
| Sex Crimes | −0.0032 | 0.0457 | −0.0701 |
| Theft/Larceny | −0.0426 | 0.0232 | −1.8364 . |
| Vandalism | 0.0180 | 0.0310 | 0.5797 |
| Vehicle Break-In/Theft | −0.0026 | 0.0168 | −0.1523 |
| Weapons | −0.0625 | 0.0447 | −1.3973 |
| Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 | | | |

*Table 3.        Results of Poisson regression for influence of number of tweets in preceding period*
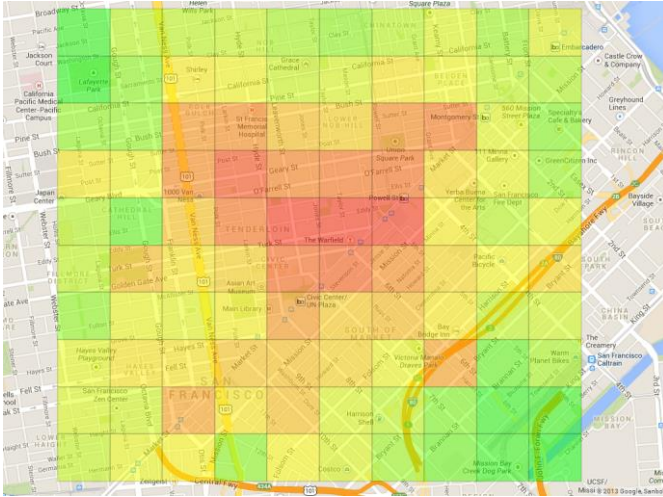


*Figure 5.        Regression intercepts for cell fixed effects colored in comparison to cell (9, 9).*

## 4.2    Predictive Analytics

The Poisson regression has provided evidence for the relationship between Twitter data and criminal activity in close temporal and spatial adjacency. As argued by Shmueli et al. (2011), *"explanatory power does not imply predictive power and thus predictive analytics are necessary for assessing predictive power and for building empirical models that predict well"*. In fact, a recent MISQ review claims that *"predictive analytics are rare in mainstream IS literature, and even when predictive goals or statements about predictive power are made, they incorrectly use explanatory models and metrics"* (Shmueli et al 2011). As a remedy, we utilize predictive analytics, which refers to building and evaluating a model aimed at making empirical predictions. Here, variables of interest are the geo-location, the time and the tweet volume. Based on these, a predictive model can draw conclusions on a logical state describing if a crime happened. While classical explanatory modeling measures the fit of a model, predictive analytics uses out-of-sample data to measure the predictive power. Thus, the model parameters are first estimated using a training set, while the predictive accuracy is evaluated on a testing set.
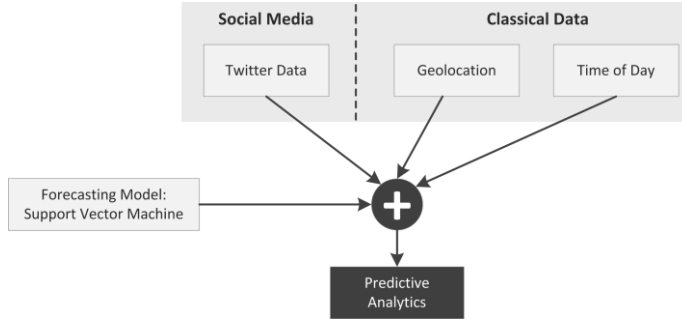
*Figure 6.      Predictive analytics combines exogenous inputs with predictive models.*

Towards generating an approach for live prediction of crimes in urban areas, we proceed as follows. We set up a Support Vector Machine (SVM) using the above data. The individual SVM is given by

$$\{C_{xy}^t \,|\, \theta_c \in \Theta\} \neq \emptyset \;\; \text{predicted by} \; \left[|W_{xy}^{t-1}|, \; a_{xy}, \; b_{h(t)}\right]^T \text{ or } \left[a_{xy}, \; b_{h(t)}\right]^T. \tag{9}$$

When training the SVM, we use a radial kernel and set the cost of constraint violation to 1. We use the first 28 days for training, while testing the predictive power on the remaining time span. The predicted variable is a logical value indicating whether a crime happened or not. Since values linked with crime are underrepresented in the data set, each class label is assigned a corresponding weight, i.e. the reciprocal proportion of occurrences. This is a common procedure in case of asymmetric class sizes to avoid possibly disproportionate influence of bigger classes on the margin. Thus, the reweighted misclassification costs are given in Table 4.

This table shows only exemplary results, however, we can see an overall trend. In the domain of predictive analytics, several metrics are used. Most simple, *accuracy* gives the ratio of correct predictions. However, more appropriate measure exists that focus on the costs related to crime incidents only. For example, the *recall* measures the ratio of predicted crimes, whereas the *precision* is the ratio of true crimes when predicting an incident. The precision can be thought of the costs when sending a police car erroneously. When predicting the occurrence of burglaries, the recall from including tweet volume drops slightly, but both accuracy and precision exhibit a visible increase. In case of predicting robberies, the results behave in the opposite manner. Though including tweet volume results in a slightly smaller precision, the recall escalates form 0.76 to 0.81.

| Predicted Variable | Model | Accuracy | Recall | Precision |
|---|---|---|---|---|
| **Burglary (logical)** | SVM including tweet volume | 0.58 | 0.67 | 0.57 |
| | SVM excluding tweet volume | 0.57 | 0.71 | 0.55 |
| **Robbery (logical)** | SVM including tweet volume | 0.66 | 0.81 | 0.61 |
| | SVM excluding tweet volume | 0.66 | 0.76 | 0.62 |

Table 4.           Predictive power of Support Vector Machines for crime incidents.

Overall, this gives the indication that the prediction of crime incidents can benefit from Twitter data as an exogenous predictor. While not every predictive power measure is superior, a boosted version can suit as a relief. Future research will show whether results are generalizable, but our early findings are very exciting and seem promising. With additional official Twitter data at hand, we will deepen the predictive analyses and select or revise additional features in detail, such as points of interest, behavioral characteristics of individuals in cities, or message topics.

## 5      Concluding Remarks

Social media data becomes more and more powerful by the ongoing increase in velocity and volume. In this research, we aimed at testing applicability of social media data, represented by Twitter messages,

for explanation and prediction of criminal activity in fine-grained temporal and spatial relationship. Data analyses anchored to this micro-level can reveal valuable information superior to the information gain of general large-area analyses, such as a virtual neighborhood watch securing tourists and residents, as well as supporting the police and authorities. In summary, we proposed an empirical analysis approach to analyze the relationship between online social user interaction and crime incidents. We collected Twitter data and recorded crimes in a fine-grained manner concerning both dimensions time and location according to an area from within the city of San Francisco. A Poisson regression was conducted that delivered evidence for a correlation between these two measures in an explanatory role. Additionally, a weighted Support-Vector Machine indicated predictability for crimes based on the hour of day and the location within the grid. Injecting Twitter data into the Support-Vector Machine led to improved prediction accuracy of crimes compared to a prediction that solely relied on temporal and spatial coordinates of crimes themselves. Thus, we showed that Twitter as a proxy for public activity in an urban area is a valuable addition for explaining and predicting criminal incidents.

According to the research questions posed at the outset, we state that mobile online social activity allows inference of unrelated societal aspects. Temporal and spatial coordinates available from social network user data reflects the public activity, which has a relation to many societal happenings, as shown for criminal incidents in this research. Furthermore, we do not only provide the explanation of incidents, but additionally provide evidence that Twitter data – even if semantically unrelated – can actually improve the prediction of crimes. Our findings can be established as a live probability-based virtual neighborhood watch, able to deliver information of increased value for tourists and residents. Furthermore, it could also be applied for optimizing planned routes of police patrol cars, since it is capable of live prediction based on social media streams.

Due to the small fraction of tweets that come along with geo-spatial information, we were only able to use around one per cent of all tweets being sent in the geographical area and time frame in question. Thus, our study is limited by the assumption that the named one per cent of tweets can serve as a proxy for the general online social activity in urban areas. Additional official Twitter data at hand supports this assumption. Given the fine-grained time slicing chosen in this work, measurement data can become sparse in areas with less social activity.

In future research, we plan to combine the newly proposed methodology with points of interest of different categories in the vicinity, such as bars, restaurants, parks, and shops, for example. Such points of interest provide a far more detailed view on the fixed effects for a certain area and we can still refine our prediction model. Behavioral characteristics of individuals in urban areas will serve as additional factors in our analyses Furthermore, instead of relying solely on temporal and spatial information, we will push automatically inferred topics from Twitter messages using Latent Dirichlet Allocation into the regression model. We will carry out future research in order to further reduce the amount of false-positives when predicting criminal incidents from online social activity. In addition, we are going to test the vicinity benchmarks with different density functions and varying cell sizes to supply a detailed benchmark measuring the robustness of our proposed method.

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