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Predicting crime using Twitter and kernel density estimation

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A R T I C L E I N F O

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Twitter is used extensively in the United States as well as globally, creating many opportunities to augment decision support systems with Twitter-driven predictive analytics. Twitter is an ideal data source for decision support: its users, who number in the millions, publicly discuss events, emotions, and innumerable other topics; its content is authored and distributed in real time at no charge; and individual messages (also known as tweets) are often tagged with precise spatial and temporal coordinates. This article presents research investigating the use of spatiotemporally tagged tweets for crime prediction. We use Twitter-specific linguistic analysis and statistical topic modeling to automatically identify discussion topics across a major city in the United States. We then incorporate these topics into a crime prediction model and show that, for 19 of the 25 crime types we studied, the addition of Twitter data improves crime prediction performance versus a standard approach based on kernel density estimation. We identify a number of performance bottlenecks that could impact the use of Twitter in an actual decision support system. We also point out important areas of future work for this research, including deeper semantic analysis of message content, temporal modeling, and incorporation of auxiliary data sources. This research has implications specifically for criminal justice decision makers in charge of resource allocation for crime prevention. More generally, this research has implications for decision makers concerned with geographic spaces occupied by Twitter-using individuals.

1. Introduction

Twitter currently serves approximately 140 million worldwide users posting a combined 340 million messages (or tweets) per day [1]. Within the United States in 2012, 15% of online adults used the Twitter service and 8% did so on a typical day, with the latter number quadrupling since late 2010 [2]. The service's extensive use, both in the United States as well as globally, creates many opportunities to augment decision support systems with Twitter-driven predictive analytics. Recent research has shown that tweets can be used to predict various large-scale events like elections [3], infectious disease outbreaks [4], and national revolutions [5]. The essential hypothesis is that the location, timing, and content of tweets are informative with regard to future events.

Motivated by these prior studies, this article presents research answering the following question: can we use the tweets posted by residents in a major U.S. city to predict local criminal activity? This is an important question because tweets are public information and they are easy to obtain via the official Twitter service. Combined with Twitter's widespread use around the globe, an affirmative answer to this question could have implications for a large population of criminal justice decision makers. For example, improved crime prediction performance could allow such decision makers to more efficiently allocate police patrols and officer time, which are expensive and thus scarce for many jurisdictions.

However, there are many challenges to using Twitter as an information source for crime prediction. Tweets are notorious for (un)intentional misspellings, on-the-fly word invention, symbol use, and syntactic structures that often defy even the simplest computational treatments (e.g., word boundary identification) [6]. To make matters worse, Twitter imposes a 140-character limit on the length of each tweet, encouraging the use of these and other message shortening devices. Lastly, we are interested in predicting crime at a city-block resolution or finer, and it is not clear how tweets should be aggregated to support such analyses (prior work has investigated broader resolutions, for example, at the city or country levels). These factors conspire to produce a data source that is not only attractive – owing to its real time, personalized content – but also difficult to process. Thus, despite recent advances in all stages of the automatic text processing pipeline (e.g., word boundary identification through semantic analysis) as well as advances in crime prediction techniques (e.g., hot-spot mapping), the answer to our primary research question has remained unclear.

We pursued three objectives: (1) quantify the crime prediction gains achieved by adding Twitter-derived information to a standard crime prediction approach based on kernel density estimation (KDE), (2) identify existing text processing tools and associated parameterizations that can be employed effectively in the analysis of tweets for the purpose of crime prediction, and (3) identify performance bottlenecks that most affect the Twitter-based crime prediction approach. Our

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results indicate progress toward each objective. We have achieved crime prediction performance gains across 19 of the 25 different crime types in our study using a novel application of statistical language processing and spatial modeling. In doing so, we have identified a small number of major performance bottlenecks, solutions to which would benefit future work in this area.

The rest of this article is structured as follows: in Section 2, we survey recent work on using Twitter data for predictive analytics. In Section 3, we describe our datasets and how we obtained them. In Section 4, we present our analytic approach for Twitter-based crime prediction, which we evaluate in Section 5. In Section 6, we discuss our results and the runtime characteristics of our approach. We conclude, in Section 7, with a summary of our contributions and pointers toward future work in this area.

2. Related work

2.1. Crime prediction

Hot-spot maps are a traditional method of analyzing and visualizing the distribution of crimes across space and time [7]. Relevant techniques include kernel density estimation (KDE), which fits a two-dimensional spatial probability density function to a historical crime record. This approach allows the analyst to rapidly visualize areas with historically high crime concentrations. Future crimes often occur in the vicinity of past crimes, making hot-spot maps a valuable crime prediction tool. More advanced techniques like self-exciting point process models also capture the spatiotemporal clustering of criminal events [8]. These techniques are useful but carry specific limitations. First, they are locally descriptive, meaning that a hot-spot model for one geographic area cannot be used to characterize a different geographic area. Second, they require historical crime data for the area of interest, meaning they cannot be constructed for areas that lack such data. Third, they do not consider the rich social media landscape of an area when analyzing crime patterns.

Researchers have addressed the first two limitations of hot-spot maps by projecting the criminal point process into a feature space that describes each point in terms of its proximity to, for example, local roadways and police headquarters [9]. This space is then modeled using simple techniques such as generalized additive models or logistic regression. The benefits of this approach are clear: it can simultaneously consider a wide variety of historical and spatial variables when making predictions; furthermore, predictions can be made for geographic areas that lack historical crime records, so long as the areas are associated with the requisite spatial information (e.g., locations of roadways and police headquarters). The third limitation of traditional hot-spot maps – the lack of consideration for social media – has been partially addressed by models discussed in the following section.

2.2. Prediction via social media

In a forthcoming survey of social-media-based predictive modeling, Kalampokis et al. identify seven application areas represented by 52 published articles [10]. As shown, researchers have attempted to use social media to predict or detect disease outbreaks [11], election results [12], macroeconomic processes (including crime) [13], box office performance of movies [14], natural phenomena such as earthquakes [15], product sales [16], and financial markets [17]. A primary difference between nearly all of these studies and the present research concerns spatial resolution. Whereas processes like disease outbreaks and election results can be addressed at a spatial resolution that covers an entire city with a single prediction, criminal processes can vary dramatically between individual city blocks. The work by Wang et al. comes closest to the present research by using tweets drawn from local news agencies [13]. The authors found preliminary evidence that such tweets can be used to predict hit-and-run vehicular accidents and breaking-and-entering crimes; however, their study did not address several key aspects of social-media-based crime prediction. First, they used tweets solely from hand-selected news agencies. These tweets, being written by professional journalists, were relatively easy to process using current text analysis techniques; however, this was done at the expense of ignoring hundreds of thousands of potentially important messages. Second, the tweets used by Wang et al. were not associated with GPS location information, which is often attached to Twitter messages and indicates the user's location when posting the message. Thus, the authors were unable to explore deeper issues concerning the geographic origin of Twitter messages and the correlation between message origin and criminal processes. Third, the authors only investigated two of the many crime types tracked by police organizations, and they did not compare their models with traditional hot-spot maps.

The present research addresses all limitations discussed above. We combine historical crime records with Twitter data harvested from all available Twitter users in the geographic area of interest. We address some of the difficult textual issues described previously (e.g., symbols and nonstandard vocabulary) using statistical language processing techniques, and we take full advantage of GPS location information embedded in many tweets. Furthermore, we demonstrate the performance of our approach on a comprehensive set of 25 crime types, and we compare our results with those obtained using standard hot-spot mapping techniques.

3. Data collection

Chicago, Illinois ranks third in the United States in population (2.7 million), second in the categories of total murders, robberies, aggravated assaults, property crimes, and burglaries, and first in total motor vehicle thefts (January–June, 2012 [18]). In addition to its large population and high crime rates, Chicago maintains a rich data portal containing, among other things, a complete listing of crimes documented by the Chicago Police Department.[1] Using the Data Portal, we collected information on all crimes documented between January 1, 2013 and March 31, 2013 ($n = 60{,}876$). Each crime record in our subset contained a timestamp of occurrence, latitude/longitude coordinates of the crime at the city-block level, and one of 27 types (e.g., ASSAULT and THEFT). Table 1 shows the frequency of each crime type in our subset.

During the same time period, we also collected tweets tagged with GPS coordinates falling within the city limits of Chicago, Illinois ($n = 1{,}528{,}184$). We did this using the official Twitter Streaming API, defining a collection bounding box with coordinates [−87.94011,41.64454] (lower-left corner) and [−87.52413,42.02303] (upper-right corner). Fig. 1 shows a time series of the tweets collected during this period and Fig. 2 shows a graphical KDE of the tweets within the city limits of Chicago. As shown in Fig. 2, most GPS-tagged tweets are posted in the downtown area of Chicago.

4. Analytic approach

To predict the occurrence of crime type *T*, we first defined a one-month training window (January 1, 2013–January 31, 2013). We then put down labeled points (latitude/longitude pairs) across the city limits of Chicago. These points came from two sources: (1) from the locations of known crimes of type *T* within the training window (these points received a label *T*), and (2) from a grid of evenly spaced points at 200-meter intervals, not coinciding with points from the first set (these points received a label *NONE*). Using all points, we trained a binary classifier with the following general form:

$$Pr\left(Label_p = T | f_1(p), f_2(p), \ldots, f_n(p)\right) = F(f_1(p), f_2(p), \ldots, f_n(p)). \quad (1)$$

[1] City of Chicago Data Portal: https://data.cityofchicago.org.

Table 1
Frequency of crime types in Chicago documented between January 1, 2013 and March 31, 2013. We excluded asterisked crimes from our study due to infrequency.

Crime type	Frequency (%)
THEFT	12,498 (20.53%)
BATTERY	10,222 (16.79%)
NARCOTICS	7948 (13.06%)
CRIMINAL DAMAGE	5517 (9.06%)
OTHER OFFENSE	4183 (6.87%)
BURGLARY	3600 (5.91%)
MOTOR VEHICLE THEFT	3430 (5.63%)
ASSAULT	3374 (5.54%)
DECEPTIVE PRACTICE	2671 (4.39%)
ROBBERY	2333 (3.83%)
CRIMINAL TRESPASS	1745 (2.87%)
WEAPONS VIOLATION	635 (1.04%)
OFFENSE INVOLVING CHILDREN	593 (0.97%)
PUBLIC PEACE VIOLATION	583 (0.96%)
PROSTITUTION	418 (0.69%)
CRIM SEXUAL ASSAULT	264 (0.43%)
INTERFERENCE WITH PUBLIC OFFICER	244 (0.40%)
SEX OFFENSE	207 (0.34%)
LIQUOR LAW VIOLATION	121 (0.20%)
ARSON	79 (0.13%)
HOMICIDE	68 (0.11%)
KIDNAPPING	58 (0.10%)
GAMBLING	27 (0.04%)
STALKING	26 (0.04%)
INTIMIDATION	25 (0.04%)
OBSCENITY*	5 (0.01%)
NON-CRIMINAL*	2 (0.00%)
Total	60,876

In words, Eq. (1) says that the probability of a crime of type T occurring at a spatial point p equals some function F of the n features $f_1(p)$, $f_2(p),\ldots,f_n(p)$ used to characterize p. We set F to be the logistic function, leaving only the $f_i(p)$ features to be specified. In the next section, we present feature $f_1(p)$, which quantifies the historical crime density at point p. Next, in Subsection 4.2, we present features $f_2(p),\ldots,f_n(p)$, which are derived from Twitter messages posted by users in the spatial vicinity of p. In Subsection 4.3, we present the model in full mathematical detail and explain how we produced threat surfaces from the point estimates of threat.

4.1. Historical crime density: feature $f_1(p)$

To quantify the historical density of crime type T at a point p, we set $f_1(p)$ to be the KDE at p:

$$f_1(p) = k(p,h) = \frac{1}{Ph}\sum_{j=1}^{P} K\left(\frac{\left\|p-p_j\right\|}{h}\right). \tag{2}$$

In Eq. (2), p is the point at which a density estimate is needed, h is a parameter – known as the bandwidth – that controls the smoothness of the density estimate, P is the total number of crimes of type T that occurred during the training window, j indexes a single crime location from the training window, K is a density function (we used the standard normal density function), $\|\cdot\|$ is the Euclidean norm, and p_j is the location of crime j. We used the *ks* package within the R statistical software environment to estimate $k(p,h)$, and we used the default plug-in bandwidth estimator (*Hpi*) with a *dscalar* pilot to obtain an optimal value for h. This standard approach is widely used by crime analysts to estimate crime densities [7].

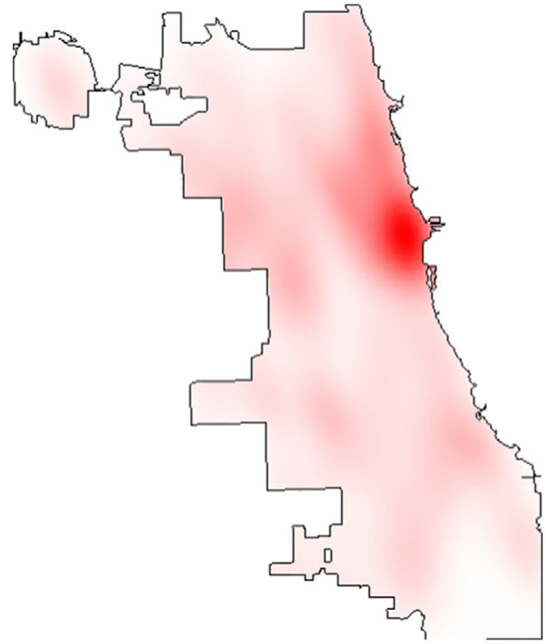


Fig. 2. KDE for GPS-tagged Tweets that originated within the city limits of Chicago, Illinois between January 1, 2013 and March 31, 2013.

4.2. Information from Twitter messages: features $f_2,\ldots,f_n$

The primary contribution of this article is an exploration of Eq. (1) for $n > 1$. That is, the novelty of this research lies in the combination of the standard kernel density estimate $f_1(p)$ with additional features $f_2(p),\ldots,f_n(p)$ that describe point p using Twitter content. Intuitively, one can think of each $f_i(p)$ (for $i > 1$) as representing the importance of topic *i-1* in the discussion that is transpiring among Twitter users in the spatial neighborhood of p, with the total number of topics being *n-1* (n is analogous to k in k-means clustering, and we describe our approach for determining its value in Section 5). We defined spatial neighborhoods in Chicago by laying down evenly spaced cells 1000 meters on each side. Fig. 3 shows the resulting neighborhood boundaries.

Given the neighborhoods defined above, the problem reduces to estimating the n-1 topic importance values for each neighborhood given

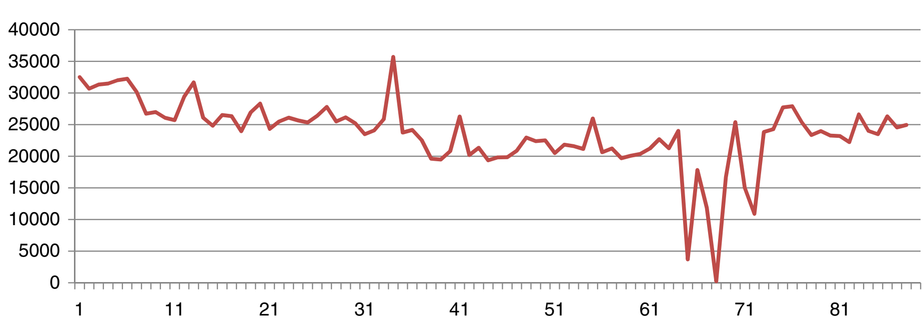


Fig. 1. Number of tweets collected daily between January 1, 2013 and March 31, 2013. The sharp spike on day 34 coincided with the United States Super Bowl. The three large drops resulted from a failure in our data collection software on those days.

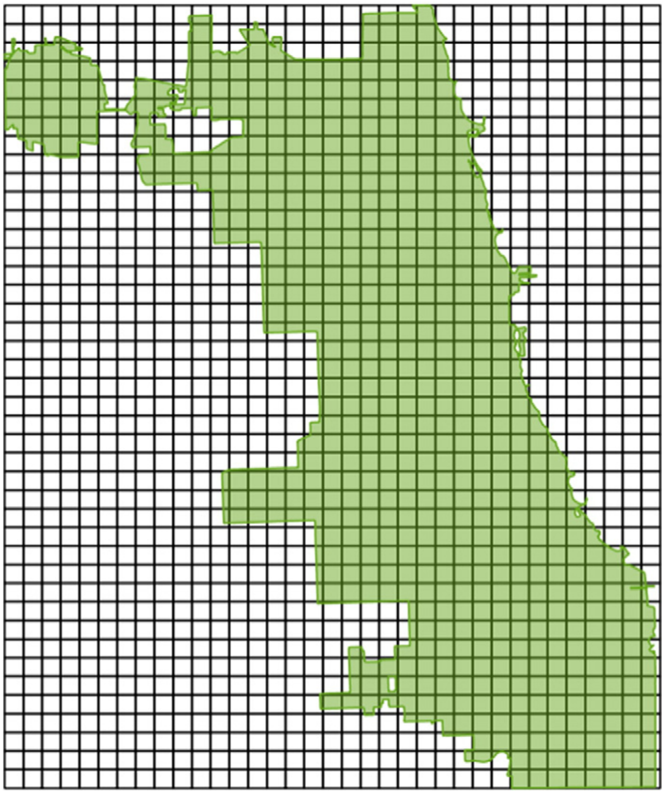


Fig. 3. Neighborhood boundaries for computing tweet-based topics. We only used the green neighborhoods (i.e., those within the city boundary) in our analysis.

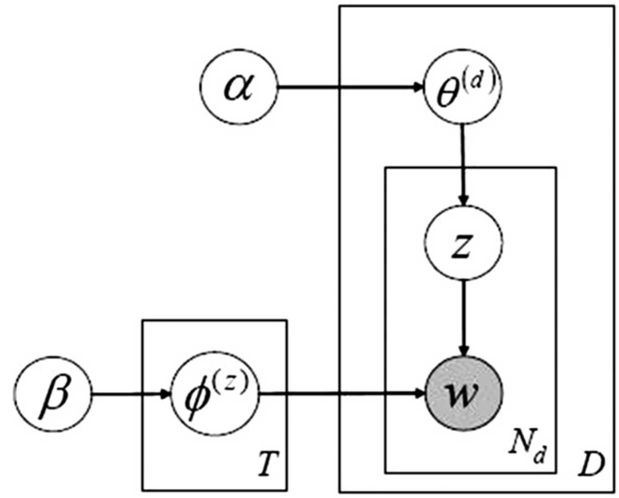


Fig. 4. Plate notation for LDA, the parameters of which are as follows: β is the hyperparameter for a Dirichlet distribution, from which the multinomial word distribution $\phi^{(z)}$ is drawn ($1 \le z \le T$), T is the number of topics to model, α is the hyperparameter for a Dirichlet distribution, from which the multinomial topic distribution $\theta^{(d)}$ is drawn ($1 \le d \le D$), D is the number of documents, z is a draw from $\theta^{(d)}$ that identifies topic $\phi^{(z)}$, from which an observed word w is drawn. z and w are drawn N_d times independently.

the tweets posted by users in each neighborhood. We used latent Dirichlet allocation (LDA) for this purpose [19]. LDA is a generative probabilistic model of textual content that identifies coherent topics of discussion within document collections. Fig. 4 shows the traditional plate notation for LDA, and we summarize the inputs and outputs below:

Documents: a collection of D textual documents with word boundaries.

Number of topics (T): number of topics to model.

Using these inputs, the topic modeling process automatically infers optimal settings for the following multinomial distributions:

Word distribution of topics ($\phi^{(z)}$): the probability that each word belongs to (or defines) a topic z.

Topic distribution of documents ($\theta^{(d)}$): the probability that each topic belongs to (or defines) a document d.

Returning to Chicago and Eq. (1), imagine compiling into a single "document" all tweets posted during the training window within a single neighborhood (see Fig. 3). The map of Chicago then defines a collection of such documents, and the topic modeling process estimates the strength of each topic in each neighborhood — precisely what we need for our crime prediction model. For example, in the neighborhood covering Chicago O'Hare Airport, the strongest topic (with probability 0.34) contains the following words:

(3) flight, plane, gate, terminal, airport, airlines, delayed, american,….

This is an intuitive result, since people often post tweets about traveling while in an airport. Thus, for any point p falling into this neighborhood, there exists a feature $f_i(p) = 0.34$. The same point p is also associated with the other T-1 topic probabilities, producing the full set of topic features $\{f_2(p),\ldots,f_i(p) = 0.34,\ldots,f_n(p)\}$ for point p. Points in other areas of the city will also have a value for f_i (the "airport topic"), but this value will generally be much lower since people in such areas will be less focused on discussing airports and travel.

LDA topic modeling is completely unsupervised, requiring no human effort to define topics or identify topic probabilities within neighborhoods. Similar to unsupervised clustering, topics do not have textual labels. Above, we labeled f_i the "airport topic" for explanation purposes only — such labels do not exist in our models. LDA also does not capture word order, making each topic an unordered set of words. For our purposes, the key output of LDA is the probability of each topic in each neighborhood. We hypothesized that these probabilities would add information to $f_1(p)$ (the historical crime density) by injecting personalized descriptions from people's everyday lives into the model. Before showing the final model formulation and describing its application, we provide additional implementation details describing how we transformed raw tweets into the topic probabilities discussed above.

4.2.1. Implementing topic modeling for tweets

Twitter is an inherently challenging source of textual information for reasons discussed earlier. Thus, deep semantic analysis of tweets via traditional methods [20] is unlikely to work well. Such methods suffer dramatic performance degradations when switching from their training domain of newswire text to the relatively clean domain of general written English [21]. We eschewed deep semantic analysis in favor of shallower analysis via topic modeling; however, we were still confronted with the problems of word boundary detection and filtering out irrelevant words (e.g., "the" and other so-called stop words). We addressed these problems using the Twitter-specific tokenizer and part-of-speech tagger developed by Owoputi et al. [22]. We processed each Tweet using this software, and we retained all tokens marked with one of the following syntactic categories:

common noun, *pronoun*, *proper noun*, *nominal* + *possessive*, *proper noun* + *possessive*, *verb*, *adjective*, *adverb*, *interjection*, *hashtag**, *emoticon**, *nominal* + *verbal*, *proper noun* + *verbal*, *existential 'there'* + *verbal*.

The list of retained syntactic categories is typical for filtering out stop words, with the exception of the asterisked categories, which are unique to the social media domain. It is particularly important to use appropriate tokenization for emoticons (e.g., ":)"), which would probably be treated as separate tokens by a traditional tokenizer but carry important semantic content describing the user's emotional state.

Once the tweets had been tokenized and filtered, we applied the MALLET toolkit [23], which outputs the following probabilities:

$$Pr(t|r) \quad 1 \le t \le T = \#topics \\ 1 \le r \le R = \#neighborhoods. \tag{4}$$

In words, Eq. (4) denotes the proportion of the discussion within neighborhood r that is devoted to topic t. Each of the R neighborhoods is described in terms of its T topic probabilities, as discussed previously. A full description of the topic modeling algorithm is beyond the scope of this article, and we refer the interested reader to the seminal presentation [19] as well as the official MALLET documentation [23].

4.3. Full model formulation and application

The full form of our crime prediction model (Eq. (1)) for crime type T, including coefficients, is defined as follows:

$$Pr\left(Label_p = T | f_1(p), f_2(p), \ldots, f_n(p)\right) = \frac{1}{1 + e^{-\left(\beta_0 + \prod_{i=1}^{n} \beta_i f_i(p)\right)}}. \tag{5}$$

For $i = 1, f_i(p)$ equals the KDE $k(p,h)$. For $i > 1, f_i(p)$ equals $Pr(i-1|r)$ from Eq. (4), where r is the unique topic neighborhood that spatially contains p. Recall that, during training, we have a set of points that are labeled with the crime type T and a set of points that are labeled as *NONE*. Thus, building the binary logistic regression model in Eq. (5) can proceed in the standard way once the density estimates and topic modeling outputs are obtained.

For any model trained according to Eq. (5), we sought predictions for crimes of type T for the first day following the training period. We obtained these predictions by evaluating Eq. (5) at spatial points across the prediction area. The set of prediction points included those obtained by evenly spacing points at 200-meter intervals across the prediction area. We also added to the set of prediction points all points where crimes of type T occurred during the training window. We added these points to force higher-resolution predictions in areas where we had observed more crime in the past. In any case, a prediction point was simply a latitude–longitude pair containing no ground-truth information about future crime.

For a prediction point p, we obtained feature value $f_1(p)$ by inspecting the density of crime T observed in the 31 days prior. We obtained feature values $f_2(p),\ldots,f_n(p)$ by inspecting the topic modeling output for tweets observed in the 31 days prior within the neighborhood covering p. At this point, the model had already been trained and the coefficients β_i were known, so estimating the probability of crime type T at point p was simply a matter of plugging in the feature values and calculating the result. Note that this only produced point estimates of threat across the prediction area. Since an individual point does not cover any geographic space, it was necessary to translate the point estimates into surface estimates. To do this, we simply recovered the 200-meter by 200-meter squares formed by the prediction points spaced at 200-meter intervals and averaged the predictions in each square to calculate the threat for each square.

Fig. 5a shows a threat surface produced by using only the KDE feature $f_1(p)$, and Fig. 5b shows a threat surface produced by adding 100 Twitter topic features $f_2(p),\ldots,f_{101}(p)$ to the KDE feature. The former appears to be smooth, since it comprises 200-meter threat squares. The latter also uses 200-meter threat squares, but any two points residing in the same 1000-meter by 1000-meter topic neighborhood will have identical topic-based feature values. Thus, most of the topic neighborhoods in Fig. 5b appear to be uniformly colored. They are not, however, as can be seen in the downtown Chicago area[2]: note the graded threat levels within many of the downtown topic neighborhoods in Fig. 5b. Such gradations are produced by changes in the KDE feature at a resolution of 200 meters.

Intuitively, the boundary between a safe neighborhood and a dangerous neighborhood in Fig. 5b should not be crisp, at least not under our neighborhood definition, which does not correlate with physical barriers that might induce such a boundary. To operationalize this intuition, we applied distance-weighted spatial interpolation to each prediction point p in the topic-based models as follows:

$$Pr_I\left(Label_p = T, W\right) = \sum_{i=1}^{|N(p,W)|} \frac{W - D(p, n_i)}{\sum_{j=1}^{|N(p,W)|} W - D\left(p, n_j\right)} * Pr\left(Label_{n_i} = T\right). \tag{6}$$

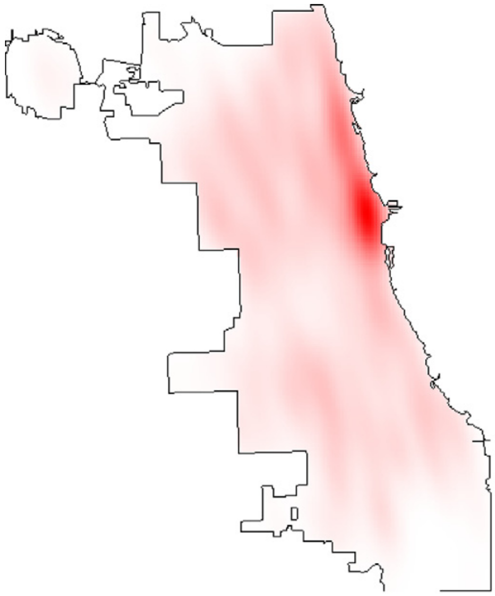
In Eq. (6), Pr_I is the probability interpolation function, W is a windowing parameter of, for example 500 meters, $N(p,W)$ is the set of p's neighbors within a distance of W (this set includes p itself), $D(p,n_i)$ is the straight-line distance between p and one of its neighbors n_i, and $Pr(Label_{n_i} = T)$ is the non-interpolated probability given in Eq. (5). Thus, the spatially interpolated probability at point p is the weighted average of its neighbors' probabilities (including p itself), and the weights are inversely proportional to the distance between p and its neighbors. Fig. 6 shows the visual result of applying this smoothing operation to the threat surface in Fig. 5b. In the following section, we present a formal evaluation of various parameterizations of the models described above.

5. Evaluation and results

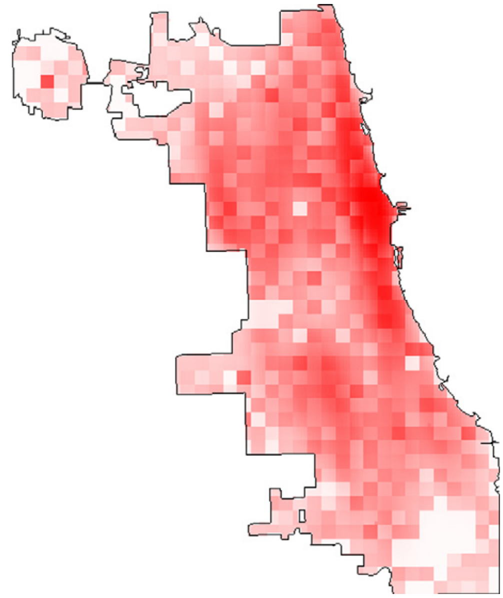
For each crime type T, we compared the model using only the KDE feature $f_1(p)$ to a model combining $f_1(p)$ with features $f_2(p),\ldots,f_n(p)$ derived from Twitter topics. We used MALLET to identify topic probabilities, configured with 5000 Gibbs sampling iterations and an optimization interval (how often to reestimate the α and β hyperparameters, see Fig. 4) of 10, but otherwise used the default MALLET parameters. We used LibLinear [24] to estimate coefficients within the logistic regression model. To counter the effects of class imbalance (there are far more negative points than positive points), we set LibLinear's C parameter to $\frac{N}{P}$, with N and P being the counts of negative and positive points in the training set, respectively. Model execution entailed (1) training the model on a 31-day window for crime type T, (2) making T predictions for the first day following the training window, and (3) sliding one day into the future and repeating. This mirrors a practical setup where a new prediction for T is run each day.

We evaluated the performance of each day's prediction using surveillance plots, an example of which is shown in Fig. 7. A surveillance plot measures the percentage of true T crimes during the prediction window (y-axis) that occur within the x% most threatened area according to the model's prediction for T. The surveillance plot in Fig. 7 says that, if one were to monitor the top 20% most threatened area according to the prediction for T, one would observe approximately 45% of T crimes. We produced scalar summaries for surveillance curves by calculating the total area under the curve (AUC). Better prediction performance is indicated by curves that approach the upper-left corner of the plot area or, equivalently, by curves with higher AUC scores. An optimal prediction sorts the 200-meter prediction squares in descending order of how many future crimes they will contain. This property makes surveillance plots appropriate for decision makers, who must allocate scarce resources (e.g., police patrols) across the geographic space. Lastly, because each model execution produced a series of surveillance plots for crime type T, one for each prediction day, we aggregated the

[2] The downtown Chicago area is the one that features most prominently in Fig. 5a.



(a) Predicted threat surface using only the KDE feature.



(b) Predicted threat surface using the KDE feature and the Twitter features.

Fig. 5. Threat surfaces without (5a) and with (5b) Twitter topics.

plots to measure a model's overall performance. For example, to compute a model's aggregate *y*-value for crime type *T* at an *x*-value of 5%, we first summed the number of true *T* crimes occurring in the top 5% most threatened area for each prediction day. We then divided that sum by the total number of true *T* crimes occurring across all prediction days. Doing this for each possible *x*-value produced an aggregate curve and aggregate AUC score, which we report in this article.

Evaluation proceeded in two phases. First, for each crime type, we optimized the number of topics and smoothing window in the Twitter-based model during a development phase. We experimented with 100, 300, 500, 700, and 900 topics and smoothing windows of −1 (no smoothing), 500, 1000, 1500, and 2000 meters. We executed each Twitter-based model parameterization for each crime type using the sliding window approach described above with an initial training period of January 1, 2013–January 31, 2013. We aggregated the evaluation results for the predicted days in February, and we used the aggregate

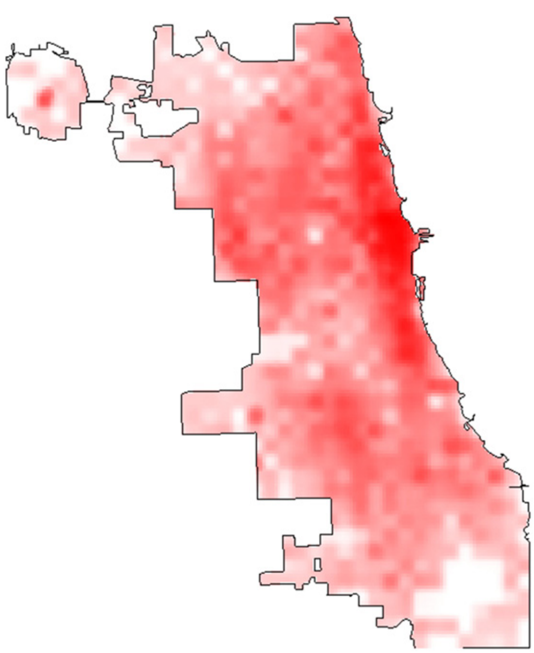


Fig. 6. Spatially interpolated surface derived from Fig. 5b according to Eq. (6).

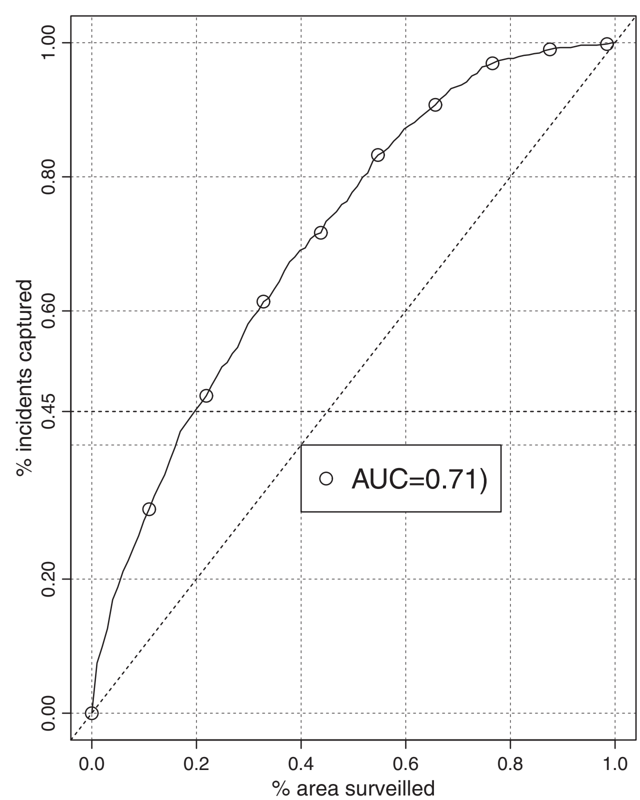


Fig. 7. Example surveillance plot showing the number of true crimes captured (*y*-axis) in the *x*% most threatened area according to the model's prediction. AUC indicates total area under the surveillance curve.

AUC to select the optimal topic count and smoothing window for each crime type. In a second evaluation phase, we executed the KDE-only model and the Twitter-based model (with development-optimized parameters) for each crime type using the sliding window approach described above with an initial training period of February 1, 2013–February 28, 2013. We then aggregated the evaluation results for the predicted days in March. The following pages show the resulting surveillance plots for the 25 crime types in our Chicago dataset. In these plots, series identifiers are formatted as "[# topics]_[smoothing *W*]", with the first value indicating the number of topics and the second value indicating the smoothing parameter. Thus, the first series "0_ − 1" is produced using the KDE-only model, and the second series is produced by a Twitter-based model with smoothing. The third series shows gains from adding Twitter topics, and the identifier for this series indicates the location of peak gain, which is shown using crosshairs at the coordinates specified. The plots are sorted by improvement in AUC achieved by the Twitter-based model versus the KDE-only model.

6. Discussion

6.1. Prediction performance and interpretation

Of the 25 crime types, 19 showed improvements in AUC when adding Twitter topics to the KDE-only model. Crime types STALKING, CRIMINAL DAMAGE, and GAMBLING showed the greatest increase in AUC (average increase: 6.6 points absolute, average peak improvement: 23 points absolute), whereas ARSON, KIDNAPPING, and INTIMIDATION showed the greatest decrease in AUC (average decrease: 12 points absolute). The average peak improvement across all crime types was approximately 10 points absolute. When interpreting the results in Fig. 8, it is important to bear in mind that, practically speaking, not all of the surveillance area (the *x*-axis) is equally important. Security forces cannot typically surveil all or even a large part of an area, making curve segments closer to $x = 0$ more relevant. Consider, for example, the crime types THEFT and NARCOTICS. Each exhibited a peak improvement of seven points absolute when adding Twitter topics and smoothing to the KDE-only model; however, this improvement was realized much earlier for NARCOTICS than THEFT (11% surveillance versus 30% surveillance, respectively).

6.2. The composition of predictive topics

In general, it is difficult to explain why crime types benefited more or less from the addition of Twitter topics. The topic modeling process is opaque and, similar to unsupervised clustering, it can be difficult to interpret the output. However, we did notice trends in our results. Looking at the first 12 crime types in Fig. 8 (i.e., those with highest AUC improvements for the Twitter-based models versus KDE-only models), we see that 9 used either 700 or 900 (the maximum) topics. We found that it was easier to interpret the topics in these finer-grained models. For example, below we list topics that were given large positive and negative coefficients for CRIMINAL DAMAGE (700 topics) and THEFT (900 topics), respectively:

CRIM. DAM. t. 128 ($\beta_{129} = 2.79$): center united blackhawks bulls ….
THEFT t. 659 ($\beta_{660} = -1.22$): aquarium shedd adler planetarium ….

These two topics are easy to interpret as sports-oriented and museum-oriented.[3] We found it more difficult to interpret highly weighted topics in models with fewer topics, for example, PROSTITUTION (500 topics):

PROS. t. 25 ($\beta_{26} = 4.60$): lounge studios continental village ukrainian ….

[3] The United Center is a large sports arena in Chicago, and the Blackhawks and Bulls are Chicago sports teams. Shedd and Adler are an aquarium and planetarium, respectively.

These anecdotal observations suggest that using more topics may improve the interpretability of the topic modeling output for crime prediction; however, future investigations will be needed to confirm this.

Lastly, Fig. 9 plots the absolute value of coefficients (*y*-axis) for topic features as a function of topic rank (*x*-axis), with topics along the *x*-axis being sorted by absolute value of their coefficients. Three crime types are shown: PROSTITUTION (500 topics), CRIMINAL DAMAGE (700 topics), and BURGLARY (900 topics). The weights are quite skewed in each series, but less so when using fewer topics. For each crime type, the most important topics receive weights that are close in magnitude to the weights assigned to the KDE features (compare the endpoints on the *y*-axis to the KDE feature coefficients shown in the legend).

6.3. Computational efficiency

The topic-based prediction model has a number of computational bottlenecks. A minor one is the tokenization and part-of-speech tagging of tweets using the Twitter-specific tagger created by Owoputi et al. [22]. This tagger is capable of tagging 1000 tweets per second on a single 3 GHz CPU core and uses less than 500 MB of RAM. Thus, we were typically able to process an entire month of GPS-tagged tweets (approximately 800,000) in 3 minutes using five CPU cores. A more serious performance bottleneck was the topic modeling process carried out by MALLET. This toolkit has been optimized for performance; however, building a topic model from a month of tweets typically took 1–2 hours, and we could not find a good way to parallelize the process since the model depends on all input tweets. Another major performance bottleneck was observed in the extraction of Twitter topic probabilities at each prediction point. We used PostgreSQL/PostGIS to store topic probabilities for each neighborhood, and even with a heavily optimized table index structure, extracting 900 topic probabilities for each of 15,000 prediction points (a single prediction) proved to be an expensive operation involving the retrieval of 13.5 million database values. This retrieval was faster than the 1–2 hours required to build the topic model, but it remained a significant contributor to the system's runtime. Our aim in this article has been to explain the modeling techniques we used and the results we obtained. We have not conducted formal runtime performance evaluations, which we leave for future work.

7. Conclusions and future work

Prior to this research, the benefits of Twitter messages (or tweets) for crime prediction were largely unknown. Specifically, the implications of GPS-tagged tweets had not been addressed, and very few of the many possible crime types had been investigated. Moreover, performance comparisons with standard hot-spot models had not been performed. We have filled in these gaps. We have shown that the addition of Twitter-derived features improves prediction performance for 19 of 25 crime types and does so substantially for certain surveillance ranges. These results indicate potential gains for criminal justice decision makers: better crime predictions should improve the allocation of scarce resources such as police patrols and officer time, leading to a reduction in wasted effort and decrease in crime response times, for example. Future work should focus on the following areas:

Tweet and network analysis: We have not analyzed the textual content of tweets beyond tokenization, part-of-speech tagging, and topic modeling. Digging deeper into the semantics of tweets could provide performance improvements compared to the models we have presented. For example, it would be interesting to analyze the predicate–argument structure of tweets in order to extract the events they describe and the actors in those events. We are not aware of such analyzers specifically designed for tweets, but many exist for standard newswire text and could be adapted to the Twitter domain [25]. We also did not investigate the various network structures within Twitter (e.g., follower–followee and @-mentions). Analyzing these networks might facilitate the anticipation of events (e.g., parties) that are known to correlate with criminal activity.

Temporal modeling: Our models do not properly account for temporal effects such as trends, lags, and periodicity. Intuitively, it makes sense that crime patterns could exhibit these behaviors and that Twitter content might be more predictive when message timestamps are taken into account. For example, one could identify trends within the topic proportions for a neighborhood and incorporate a trend variable (e.g., magnitude of increase or decrease) into the model. One could also allow for delayed effects of Twitter topics, the intuition being that Twitter users often anticipate crime-correlated events

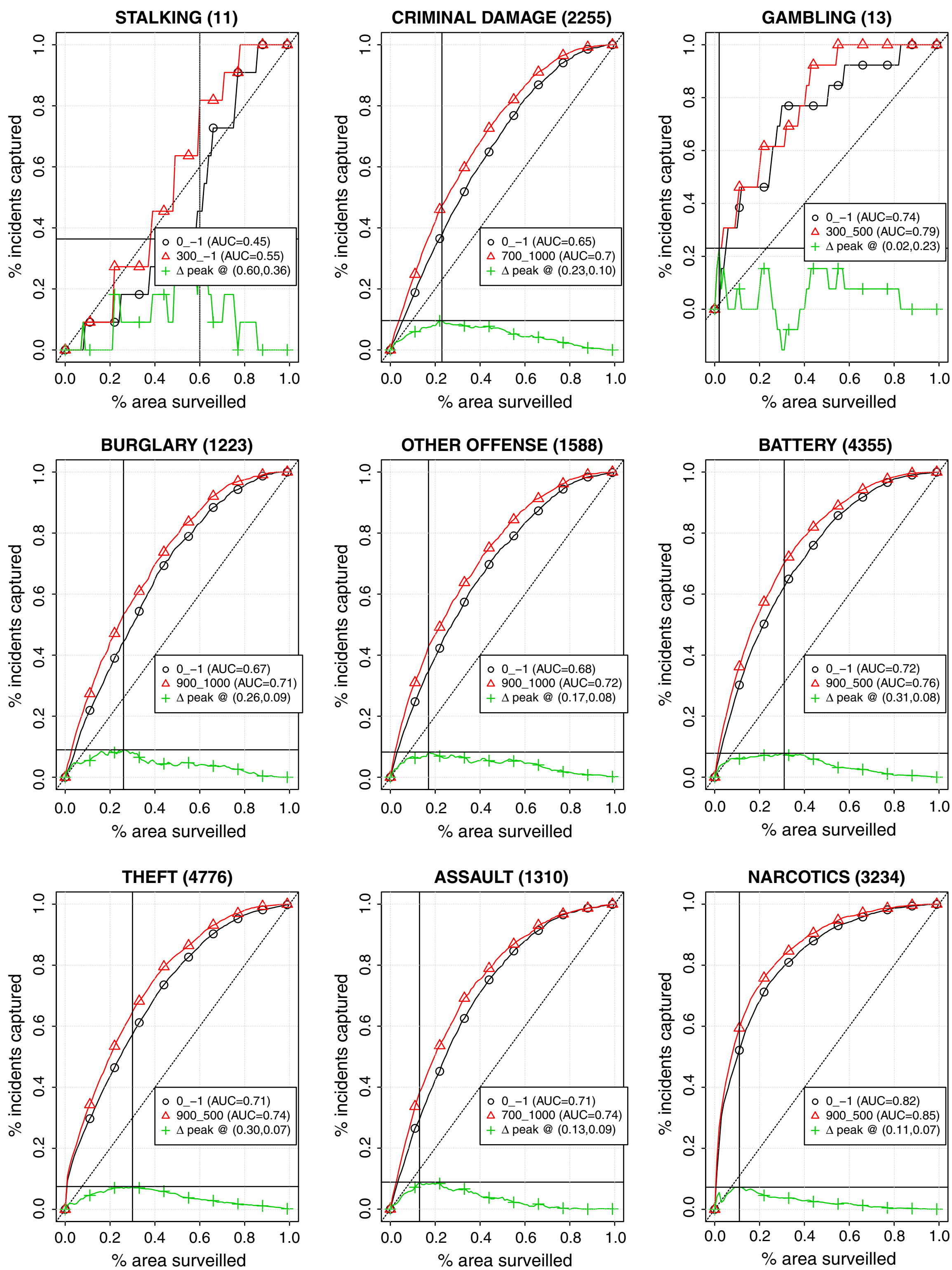


Fig. 8. Surveillance plots using KDE-only (series 1) and KDE + Twitter (series 2) models. Series identifier format: [# topics]_[smoothing *W*]. Series 3 shows gains from adding Twitter topics. Peak gain is shown using crosshairs at the coordinates specified.

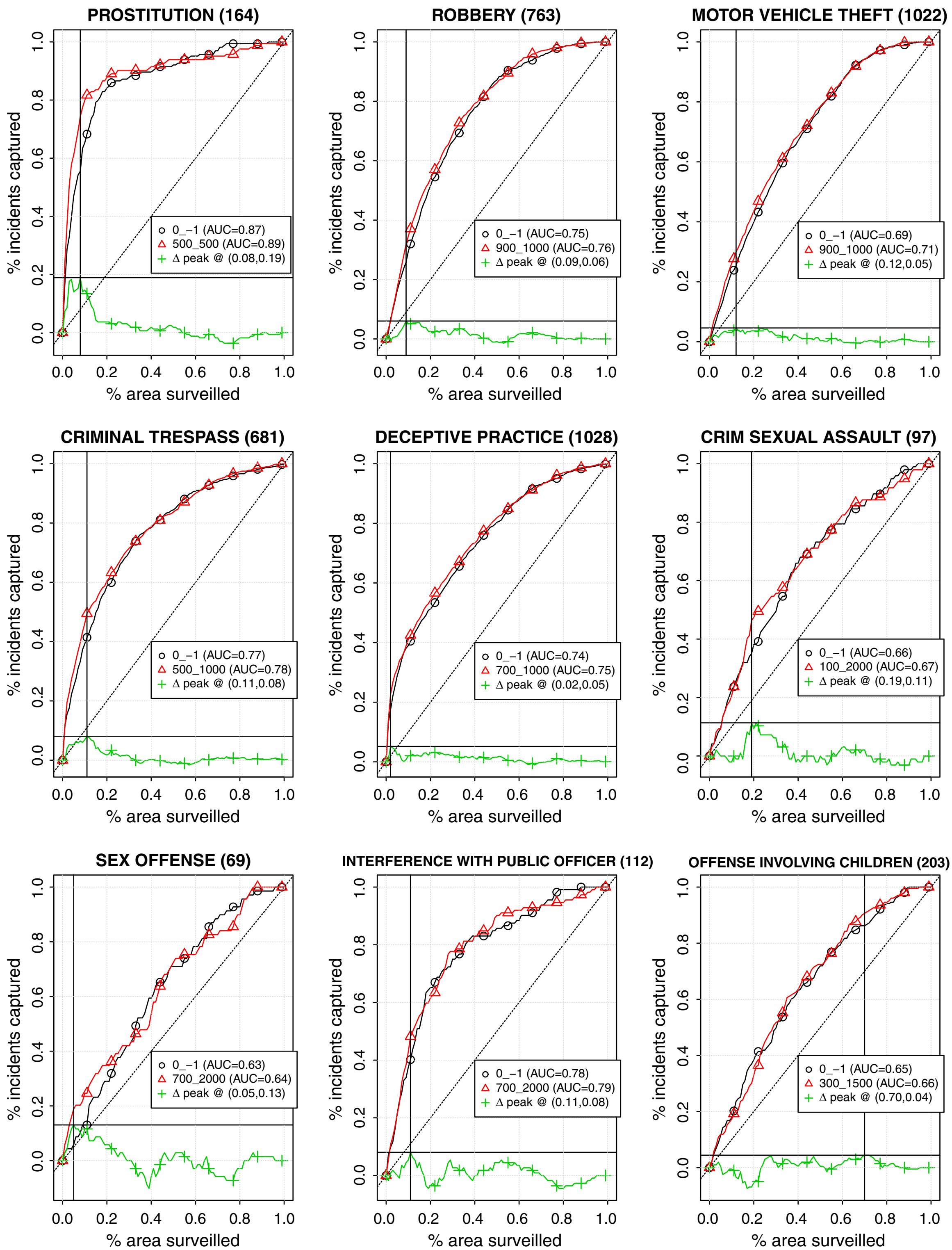


Fig. 8 (*continued*).

(e.g., parties) when they compose their messages. Lastly, we did not explore alternative modeling techniques like random forests, which are capable of handling non-linear threats.

Incorporation of auxiliary data: Our modeling paradigm is able to accommodate an arbitrary number of additional features. For example, prior work has investigated various spatial and socioeconomic features [13], which might complement the KDE and Twitter-based features we used in our models. The City of Chicago maintains a large, public repository of auxiliary datasets that could be incorporated into the models. Given the number of available auxiliary datasets,

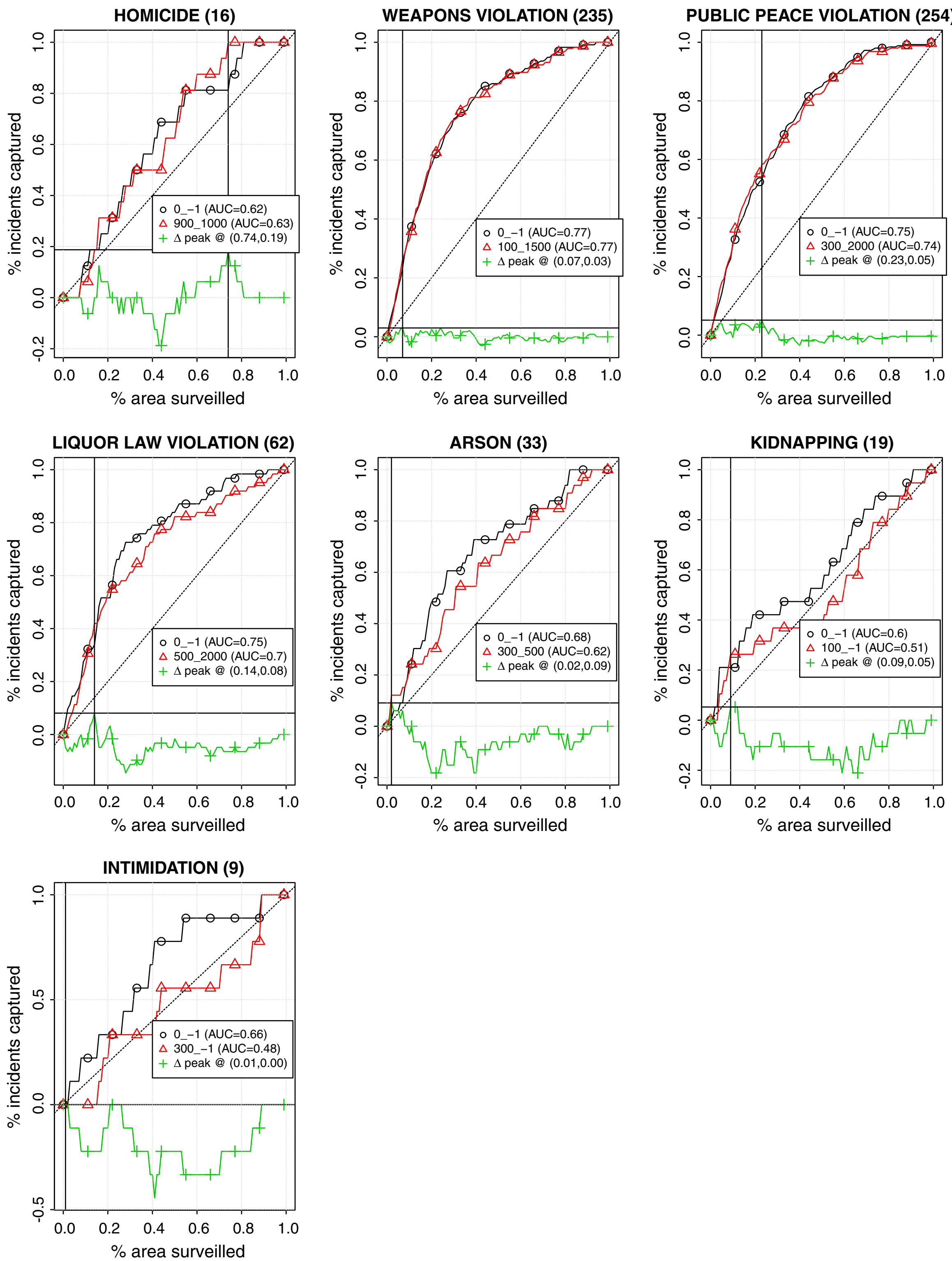


Fig. 8 (*continued*).

future work will need to focus on scalability. We do not expect our PostgreSQL/PostGIS configuration to support feature extraction from hundreds of spatial datasets for thousands of prediction points. Newer, non-relational data management techniques (e.g., NoSQL) could provide a more scalable solution.

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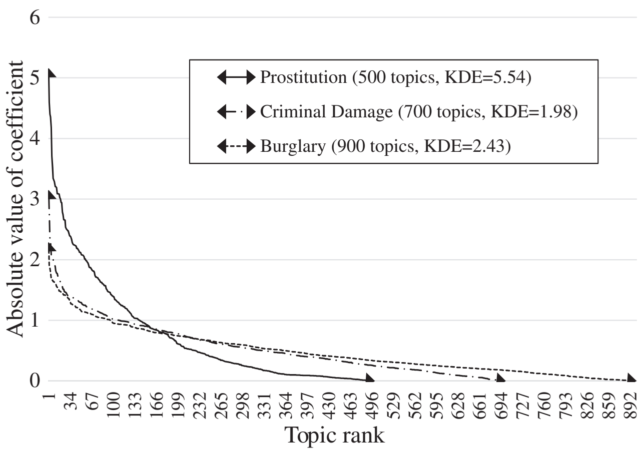

Fig. 9. Logistic regression coefficients assigned to Twitter topics for three crime types. The *x*-axis denotes the rank of the topics when sorted by absolute value of their coefficients (the *y*-axis). The legend indicates the number of topics used for the crime type as well as the absolute value of the coefficient assigned to the KDE feature.

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