Through the Looking Glass: The Promise and Peril of Crime Prediction

Christian Vazquez[1], Laya Anasu[2], and Suzanne Wang[3]

Abstract— **Employment of crime predictive technology is steadily growing in use by law enforcement entities to better manage resources and prevent criminal activity. However, despite the capabilities of machine learning models to predict dangerous localities effectively, very few systems are targeted towards the general public. We present a system that leverages data from criminal incidents, demographics, and miscellaneous qualities about a locality (e.g. proximity to establishments) to provide prediction of robberies in the city of New York within quarter-daily windows of time. We describe a mobile platform that could leverage the predictive capabilities of the system, and provide a visualization tool to explore the criminal landscape of NYC and view the predicted robberies. Furthermore, we discuss the social impacts that could result from the adoption of crime predictive technologies by the general public including: the stigmatization of dangerous areas, impact on economies, and the capacity of these tools to become enablers of criminal activity. We close by proposing a simulation framework that could be utilized to test the assumptions presented in the discussion of social implications and highlighting possible directions for the future of crime predictive technologies.**

I. INTRODUCTION

Research on "crimes of place" suggest that visiting certain locations can make individuals more susceptible to crime [1]. Wrong-Place/wrong-time incidents like the murder of Stephanie Kuhen [2], where a family unconsciously wandered into the wrong neighborhood, show how a wrong turn can have tragic consequences. People who lack location-based insight of a place (e.g. tourists) are particularly vulnerable to crimes of place. Predictive crime technologies have been developed in the past, taking advantage of crime's highly spatiotemporal components and characteristics about a certain locality to determine which areas are more susceptible to criminal activity (i.e. Criminal Hotspots). Although existing solutions have shown effectiveness in determining criminal Hotspots, they have mostly been catered to law-enforcement entities. As so, their capability to predict crime has been limited to coarser grained windows, allowing the interested parties to manage their resources more efficiently across long periods of time.

In this work, we present a Crime Prediction system aimed at the general public. We intend to enable interested parties with a criminal forecasting tool that allows for a more conscious traversal of new places, within a finer grained temporal window. Our goal is to allow the means for people to proactively avoid zones of danger. For the purpose of the study, we focus on criminal activity in New York City (NYC), and limit the category of predicted crimes to robberies. We follow with the description of the distinct data sources that were utilized to train our predictive model, the process used to pair criminal/feature data to a discrete area of study, and the challenges of dealing with a highly imbalanced set of data. We highlight the process of training a predictive model using neural networks to achieve crime prediction within hourly and quarter-daily time windows. The results of our system are presented by testing predictions on the same year it was trained on (within-year) and testing predictions of years to come (across-year). Additionally, we discuss the implementation of a mobile system that can leverage the capabilities of our system to the general public and present a visualization of the criminal forecast as a web interface. Finally, we turn our discussion towards the societal implications of developing criminal forecast systems that label dangerous areas to the general public, highlighting the capability for stigmatization and segregation and its potential consequences. We present sensible solutions to mitigate the existing dangers and close describing mechanisms by which the potential dangers could be more tangibly explored through simulation.

II. RELATED WORK

As our work includes both building a predictive model and creating a user-facing application, related work that is relevant to our paper includes both academic research and actual technologies implemented by law enforcement.

A. Academic Research

Current research surrounding crime prediction using machine learning techniques focuses on two main areas: prediction of crime by time and location and by individual or groups. The latter is especially relevant for questions surrounding recidivism: estimating the likelihood of an individual to be a repeat criminal offender. Furthermore, this focus can help detect patterns of crimes among individuals and groups. This paradigm was explored in Wang et al's paper [5], which proposed a pattern detection algorithm to help determine which crimes may have been committed by the same individuals or groups. However, as our paper seeks to predict crime by location, research focusing on spatial prediction is more relevant.

Recent research has utilized data capturing human footfall and density within urban areas. Bogomolov et al [7] worked with anonymized human behavioral data from mobile network activity along with demographic data to predict crime by location. Otherwise known as the Smartsteps dataset, the mobile network activity data captured certain demographics and the purpose (e.g. working, visiting) of people as they moved between locations in London. They used a decision tree classifier based on Random Forest to build the model, finding that human behavioral data from mobile phone activity drastically improved the prediction accuracy. Traunmueller et al. [9] has also used mobile phone data to capture footfall by location and time of day, examining different theories of urban crime.

Other papers have used kernel density methods with strong results. Chainey et al [6] used hotspot mapping to predict spatial patterns of crime: burglary, street crime, theft from vehicles and theft of vehicles. Among their methods, kernel density estimation consistently outperformed all other mapping techniques to predict where crime would occur. Matthew Gerber [8] has worked on predicting crime with Twitter, incorporating linguistic analysis into a kernel density crime prediction model. Almanie et al [14] also focus on finding hotspots of crime by time and location, using Decision Tree and Naive Bayesian classifiers to predict potential crime types.

Examining crimes related to ambient populations has been of interest to researchers, moving beyond just residential population in a particular location to capture a more accurate portrait. A recent paper by Malleson and Andresen [10] sought to capture the complexity of how crime impacts different types of people. They use spatio-temporal cluster hunting techniques, incorporating mobile and Twitter data, to identify crime hotspots that are significant for the ambient population. Similarly, new research published in October 2016 by Kazumasa Hanaoka also focus on the ambient population through mobile phone data. Research based in Japan found crime patterns to change temporally and based on population density within a certain area. This population is of particular interest to our paper, as our Know Your Area application is intended for use by such groups.

On the social side, Tayebi and Glasser [12] also recently published a book, *Social Network Analysis in Predictive Policing*, which uses social network analysis in crime prediction models. For example, examining co-offending networks of people who have committed crimes together, relying heavily on their networked relationship to predict crime. A recent paper by Lepri et al. [13] has focused on the unintended social consequences of using data for social good, including the consequences of predicting criminal behavior and crime hotspots. They point out problems with indirect discrimination, privacy, etc in such algorithms, similar to many of the concerns our paper raises.

B. *Crime Mapping Applications*

Crime mapping applications focus on presenting the localities of criminal activity or statistics about an area of interest by overlaying the information graphically on a map. Many of these focus primarily on historical data, making no assumption on the relative safety of an area. In essence, crime mapping applications suggest that the data ”speaks for itself”, taking no stance as to whether previous history of crime is indicative of future criminal activity. The benefit of these technologies is that they are easy to understand by the general public, and can be implemented with relative ease, so long as the data is available. In the US market, there are similar applications that provide lists of crimes committed around the users location. Among them is SpotCrime, which provides current events and breaking crime stories around the user [17]. Localcrime keeps their users informed about crimes or wrongdoing in their neighborhood [18]. CrimeReports gives access to neighborhood level crime and sex offender information[19]. Nevertheless, the presented layers are highly spatial and incapable of predicting criminal activity in new places.

C. *Crime Prediction Technologies*

Crime prediction technologies, as the name suggests, focus on determining from distinct factors whether a crime is likely to happen at a particular location. Similar to Criminal Mapping Applications, most crime prediction technologies make use of historical criminal data to model future criminal activity. However, other factors are utilized to further generalize predictive capabilities. Unlike Crime Mapping Applications, predictive technologies take a stance, taking the data and suggesting the possibility of crime in a particular area, possibly using mapping layers to visualize some probability metric on top of the area under study.

Series Finder [5] has been implemented in the Cambridge Police Department, finding patterns of crimes already identified by the PD. It was also able to identify nine additional crimes that the PD did not previously know about. [15]

There are also companies focused on bringing predictive policing models to law enforcement. PredPol, founded in 2005, works with groups like Atlanta Police Department and the LAPD. Research conducted by Mohler et al [16] through randomized field trials found predictive policing to be effective in reducing crime rates. Competitors, including the HunchLab, spun out of Avazea Labs in Philadelphia. Though our application is not intended for law enforcement, such implementations shed light on questions surrounding usage of crime prediction algorithms in real life.

III. DATA SOURCES

The developed system primarily makes use of criminal incident records in order to predict future crime. In addition to criminal incidents, several features were explored and paired with the criminal historical data to enhance the system's predictive capabilities. What follows is a description of all the different sources of data that were utilized to train our system.

A. *New York City Criminal Dataset*

The NYC Open Data initiative releases useful information from different city agencies for public use. This initiative provides useful datasets for the following categories: Education, Environment, Health, Housing and Development, Public Safety, Recreation, Business, City Government, Social Services, and Transportation. For the purpose of this study, we focused on using the Public Safety data as the cornerstone for our predictive model. More specifically, we utilized a collection of criminal incident entries ranging since 2001 to 2015, containing more than a million entries of criminal incidents. Each data entry was composed of the location of the crime depicted in coordinates (latitude and longitude),the type of crime that was committed, a time-stamp that depicted the moment the crime happened, a brief description of the event, and several police codes used to classify the criminal offense. The data was subsequently filtered twice. First, all crimes that happened before 2006 were removed, primarily because the reporting was inconsistent and only showed a very small amount of crimes happening for the earlier years. Subsequently, we removed all crimes that were not of the classification of robbery (both armed and unarmed), leaving us with about 195,000 entries to train our system.

B. Google Places API

The Google Places API provides location awareness to mobile platforms, giving information about establishments in the near vicinity given a latitude-longitude pair and a search radius. This information was collected by querying the Places service at different locations in the area under study. More specifically we focus on the total number of establishments within a certain radius and the number of establishments by type (e.g. bars, restaurants). This information was collected and paired to our criminal incident entries to provide better profiling of the locality where the crime occurred.

C. IEM Historical Weather Data

Previous studies[24] have shown correlation between weather patterns and the incidence of certain crimes. For the purpose of our study, we were interested in using weather features correlated with the criminal incidents. Generally, robberies occur outdoor, when a victim is commuting to a particular destination. Given weather patterns affect human mobility, we gather historical weather data under the assumption that it can be used as a predictive feature. Given our criminal data set ranges from 2006 to 2015, we required to obtain historical weather data of a similar range. Additionally, the temporal granularity of the criminal reports required that the weather information be collected on an hourly basis. The Iowa Environmental Mesonet (IEM)[26] collects environmental data from a wide variety of sensors across the country at distinct levels of temporal granularity. These range from minutes to days, making it suitable for our purposes.

D. Street Score

The Street Score[20] project is a collaboration between Macro-Connections and Camera Culture group which aimed to generate an algorithm that could score the perceived safety of a location based on an image. In order to train this algorithm, the project crowd-sourced score responses from human subjects subjected to different images of streets and locales from different cities. The resulting responses were aggregated to create a ”perceived safety” score for different points through the city of Boston, New York, and Detroit. Studies have shown that the collective gut of the masses is a very powerful tool, often tapping into unconscious (possibly biased) hunches about a certain topic. We trained a version of our system by embedding it with this ”collective gut” of the participants of the Street Score study, in order to see if human perception is capable of predicting whether or not a locality is dangerous.

E. 2010 Census Demographic Data

We include demographics data obtained from the 2010 census as features for our model. This includes information at the granularity of Census Tracts about wealth, race, population, and several other fine-grained features about our area under study. The Census Demographic data is available at different spatial granularity: state, county, place, and census tract. We chose to obtain the aggregated data at the granularity of census tract, which proved to give the highest variability within the different areas of the city of New York. The data, which contained around 6000 features, was then mapped to an overlaying grid as described in the following section.

IV. EXPLORATORY DATA ANALYSIS

Prior to modeling the system for Crime Prediction, we analyzed distinct data sources in order to gain insight that would enhance the modeling process.

A. Temporal Patterns

Consistent with other research on the subject, we find that number of reported robberies in NYC has decreased overall from over 23,000 in 2006 to less than 16,000 in 2015, with slight increases in 2008, 2010, 2012, and 2015.

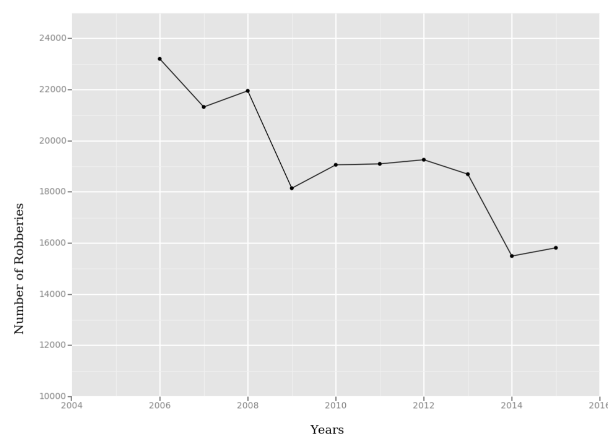

Fig. 1. Reported robbery incidents in New York City, 2006-2014.

Adjusting for number of days, we also find that reported robberies are lowest in February and highest in October overall, with rates steadily increasing in the warmer months between May and October then falling as the weather gets colder.

B. Street Score

We examined the data from StreetScore using their q-score metric, which predicts how safe the image of a street looks to a human observer based on a crowdsourced survey called Place Pulse. After mapping and averaging the q-scores to our grid, we found that the perceived safety of a location has virtually no correlation with the number of robberies. In fact, in 2014 the grids with the highest crime had average q-scores.

This showed that human perception was not necessarily accurate in predicting the actual danger of a location, and more accurately assessing the safety of a location required understanding more features.

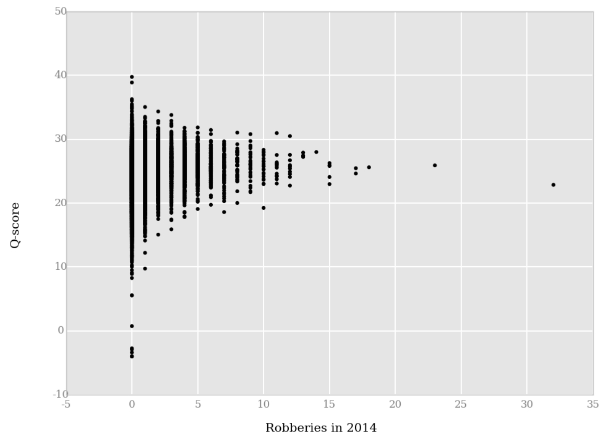

Fig. 2. Q-score and NYC robbery in 2014

C. Google Places Data

Adding in data from Google Places API, we found number of establishments within each grid to be a relevant feature in predicting crime. Areas with a higher number of robberies were by and large relatively less populated by businesses, including by bars, restaurants and stores.

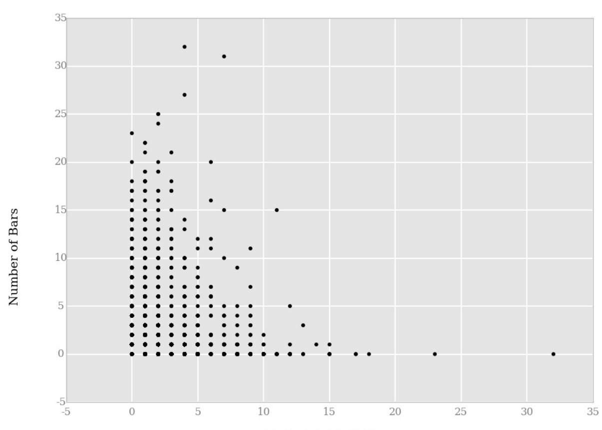

Fig. 3. Number of bars and NYC robbery in 2014

D. Census Data

The census data, with its over 8,000 features, provided information about the demographics of tracts within New York City, including race, gender, and household status. Through forward stepwise regression selection, we found that household living situations in a particular area, specifically the percentage of single women renting alone, had an impact on number of robberies occuring in that area. Based on a simple regression, single female renters accounted for 0.26 of the variance of crime in 2014 with a t-statistic of 15.95 and coefficient of 0.030, indicating that the types of residents matter in understanding the criminal landscape as well. For example, crime is less likely to occur in areas more populated by homeowner families relative to areas with more single female renters.

V. Creating the Dataset

A. Building the Grid of NYC

In order to create a predictive model for NYC robberies, we needed to define the domain for the spatial understanding of our model. Crime occurs in continuous coordinate space, namely latitude and longitude pairs. We required to divide our area of study (NYC) into several discrete localities. Several techniques exist to achieve this in crime mapping technologies at different granularity. For instance, kernel density mapping creates a continuous forecast space, using clustering to portray the density of crime in a locality. Other techniques involve dividing the area of study by theme in a discrete fashion. Thematic mapping refers to dividing the city of New York into corresponding areas that represent a higher level ordering such as boroughs, neighborhoods, streets, or census tracts. One disadvantage of thematic mapping is that the resulting subdivisions are of distinct area, thus making the comparison less intuitive between forecast on distinct places. A common alternative is to use Grid Thematic mapping, which overlays a grid over the city of arbitrary but constant grid size. Given our system is targeted to the general public, and we are interested in enabling safe commuting throughout NYC, it seems sensible to use grid thematic mapping to provide fine-grained spatial knowledge that can be aggregate in simple units to plan a commuting trajectory. It is also essential that the metric presented is fairly intuitive and allows a person with no technical knowledge to generate a commuting plan.

Figure 4 shows the process of creating the grid over NYC for classification purposes. First, an arbitrary grid is layered on top of the area of study. Each grid is represented in the data as the center latitude-longitude pair in continuous form. Data points are then mapped with the distinct grids, allowing the system to classify accordingly. The grids are stored as GeoJSON, an encoding format for geographic shapes/areas using latitude and longitude pairs. In order to map data to the grids efficiently, the GeoJSON are pushed to a schema-less MongoDB database, which supports spatial queries. Using the location of the criminal incident, we iterate over the entire crime dataset and assigned it the center longitude and latitude of the grid where the incident took place.

B. Mapping Data to Grid

A similar process is achieved for the Streetscore dataset, the census demographic data, and the Google places API. For the Streetscore dataset, all the values of perceived safety for localities that fall within a grid are averaged and assigned to the grid. The census demographic data is partitioned by census tract. Conveniently, the census office provides shape-files that allow us to identify to what census tract the corresponding grid belongs to. We assign each grid a census tract id and use it to pair with the data for that particular area. Finally, we utilize the Google Places API to query for all the distinct locale and locale types within a GeoJSON grid. All this information is stored on a per grid basis in the Mongo database. The resulting grid structure consisted of 33,405 grids of about 20 km squared.

Fig. 4. The process of applying grid thematic mapping to NYC. Create arbitrary grid, map the crime to the individual grids, and classify areas accordingly

C. Data Aggregation by Time Window

In order to train our predictive system, we needed to consider carefully the way data would be aggregated or binned together in our final input vector. The granularity plays a significant role in determining the usefulness of our classifier. For instance, binning the expected crime by week or month would be useful if the objective of the user was to manage or distribute policing resources. However, given our target is the general public and this is intended for commuting purposes, we needed to define a finer window of time. It is important to note that as the window shrinks the classification becomes a harder task. The original system was implemented for hourly predictions. However, after considerations regarding the accuracy of the system, a more sensible window of time was selected. The day was divided into four sections:

- Early morning: 12:00am - 5:59 am
- Morning: 6:00 am - 11:59 pm
- Afternoon: 12:00 pm - 5:59 pm
- Night: 6:00pm - 11:59 pm

Therefore, each input vector would represent the number of crimes that happened during an time bin in a particular grid (depicted by the center latitude-longitude pair), on a daily basis. In other words, there exists a sample for each hour bin in a day, for every grid in the area of study. Each sample is referred to, for the remainder of the paper, as a grid-day-time triple.

D. Generating Zeros

The data available from the criminal incident database for NYC only include entries for all the crimes that happened between 2006 - 2015. Once our criminal incidents were aggregated by quarter daily bins, we found that most grids only included one or no crimes per sample. As so, in order for our system to learn to distinguish between grids where crime will or will not occur, we needed to generate a complementary data set which listed zero crimes for a particular grid-day-time bin triple. As previously mentioned, there exists 33,405 grids. Therefore, each day there would be (time bins) 4 x 56,000 grids. Given our data set contains criminal data for 9 years (2006 - 2015), the resulting size of all the samples would be 365 x 4 x 33,405 x 9 = 438,941,700. Given computational limitations, it was intractable for us to generate the full data set for the modeling. As so, a sampling mechanism was implemented to under-sample uniformly with replacement the grid to generate no-crime samples.

VI. MODELING FOR CRIME PREDICTION

Two different approaches were explored during the training of the predictive model. First, a binary classification system was generated that predicted whether a crime would or would not happen on a particular grid on a particular hour bin of a day. The second approach was a regression problem for which our system outputs the expected number of crimes for a particular hour-bin-day in a grid. The binary classification metric facilitates understanding for the user, however imposes a more significant stance regarding the resulting system's output. Using a regression method afforded a more distributed representation of crime (measuring different grids as different levels), however, the metric is not as simple to understand. What does it mean for it to be 0.35 expected number of crimes for a particular grid-bin-day triple? We can tackle this problem by creating a quantile mapping for every grid-daytime triple, allowing us to classify the danger of a zone relative to all the grids in the area under study.

A. Handling the Imbalanced Problem

The number of day-grid-hour triples on which crime incidents occurs throughout the NYC criminal incident dataset from 2006 to 2015 is about 192,000. As previously mentioned, the number of no crime triples for this dataset is therefore about 735,840,000. Needless to say, this represents a severely imbalanced dataset, where the instances of crime occurring (class 1) is disproportionate to the instances of

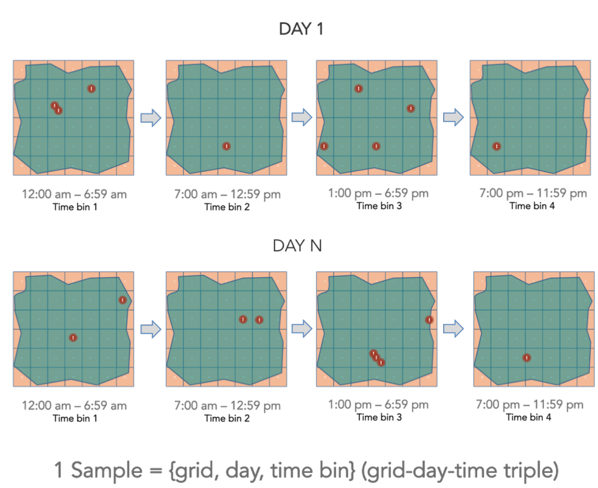

Fig. 5. Defining grid-day-bin triples by sampling each grid daily at each time bin.

crime not occurring (class 0). As a result, the minority class is not represented fairly in the dataset.

Much literature exists on distinct techniques for handling imbalanced datasets [21], [22], [23]. In essence, the most common approaches to tackling the unbalanced problem revolve around the following: under-sampling, oversampling, weighting your loss function. Under-sampling refers to partially selecting samples form your majority class (in our case class 0) such that the proportion in the training set is better distributed. Conversely, oversampling suggests duplicating or generating samples from the minority class to achieve a similar effect. Another commonly used technique is weighting your loss function such that the cost of not recognizing the minority class is higher than the cost of the majority class.

For the purpose of this work, oversampling requires availability of the full dataset (735,000,000+ entries), which we already deemed intractable for the available computing resources. Therefore we trained our system by combining under-sampling the majority class uniformly across the grid and assigning a higher weight to the minority class. Another important thing to consider when handling the imbalanced problem is the metric utilized to report the system's accuracy. Certain metrics, such as accuracy, can be misleading in datasets that are imbalanced. For instance, the system can still achieve a high accuracy by guessing no crime will happen given the distribution of crime/no-crime triplets. For the purpose of this work, we chose to focus on recall and precision for both classes, as well the area under the receiver operating characteristic curve (ROC).

B. Model Selection

The problem of predicting crime was tackled using a fully connected neural network with two hidden layers. The neural network was modeled using Keras which implements a python wrapper on top of Google's Tensor flow back-end and is compatible with the sci-kit learn library. The Adam optimizer was used to train the system for various scenarios. For the regression problem, the metric for optimization utilized was the mean squared error, while for the binary classification problem binary cross entropy was selected as a suitable option. The topology of the network was kept the same for both the binary and regression problems. However, the output node of the binary classification problem used a sigmoid activation while the regression problem did not. The model pipeline scaled the input features (adjusted to have mean 0 and variance 1). Additionally, PCA was utilized to reduce the feature space of census demographic data from 6,750 features to about 100 components.

VII. RESULTS

The implemented system was tested under two different conditions. The first condition determines the capacity to predict crime using data from the same year from which crime will be predicted. We call this the within-year scenario. We also test the capacity for the classifiers to generalize across years, which we call the across-year scenario. Both within-year and across-year problems were evaluated using cross-validation. For the within-year scenario, ten-fold cross validation was applied to each year and evaluated for the binary classification problem. The across-year validation was exercised by permuting the training set with all the years minus one using a Leave One Out (LOO) strategy. The following table shows the results for both scenarios. Note that the within-year was only evaluated for the binary classification problem, whereas we report results for regression and binary classification in the across-year table. The metric used to present regression results is the mean squared error. Precision, recall, and f-measure show the results for the binary classification problem.

TABLE I
WITHIN-YEAR EVALUATION OF CRIME PREDICTION

Year	Precision	Recall	FMeasure	ROCAUC
2006	67.60	70.76	69.12	85.88
2007	66.90	68.20	67.51	86.01
2008	68.06	68.84	68.43	86.43
2009	65.25	60.18	62.59	85.80
2010	66.16	63.16	64.61	86.07
2011	65.70	63.84	64.72	85.80
2012	66.10	64.54	65.28	86.07
2013	65.77	63.27	64.47	85.85
2014	63.58	58.37	60.83	85.83
2015	64.75	59.69	62.07	86.08

TABLE II
ACROSS-YEAR EVALUATION OF CRIME PREDICTION

Year	Precision	Recall	FMeasure	ROCAUC	MSE
2006	69.40	72.43	70.88	87.31	0.1420
2007	69.33	69.23	69.28	87.63	0.1366
2008	70.55	67.96	69.23	87.73	0.1360
2009	65.28	69.13	67.15	87.38	0.1326
2010	68.31	65.17	66.71	87.58	0.1334
2011	67.74	65.22	66.45	87.33	0.1356
2012	68.65	64.99	66.77	87.55	0.1330
2013	68.14	63.23	65.59	87.41	0.1320
2014	65.34	61.94	63.60	87.35	0.1269
2015	65.60	63.83	64.70	87.55	0.1271

We additionally explored how performance changes when testing against a more severely balanced dataset that represents reality more accurately. The results for binary classification using ten-fold cross validation on the totality of the dataset are presented below in a similar format:

TABLE III
ACROSS-YEAR EVALUATION OF CRIME PREDICTION (IMBALANCED)

Case	Precision	Recall	FMeasure
Balanced	67.91	67.38	67.63
Imbalanced	38.00	69.04	49.01

VIII. DISCUSSION

The system was tested using different combinations of features. However, the results presented in the previous section constitute training our model with all the features discussed in the exploratory sections of this work: time, location, Google places, Weather, and Census Demographics data. The initial model, trained only on spatiotemporal features of past criminal incidents, showed a high dependence on the latitude-longitude pair where the criminal incident took place, achieving relatively decent scores for the task. After initial testing with this spatiotemporal baseline model, we added weather, census and Google Places API data in that order to increase the predictive capability of our model. Due to the high dimensionality of the census data, we opted to use principal component analysis(PCA) to reduce the number of features in the modeling process. We evaluated the model using all the features while varying the amount of selected components yielded by PCA. The best performance was achieved using the first 100 components.

Not surprisingly, the spatial features (census data, latitude, longitude,and Google Places API data) offered the most improvement for the selected classification metrics. These results are validated by Hotspot theory, which suggests crime is highly localized and its spatial distribution can be exploited by predictive models. The Google Places API data proved to be very effective in developing a more accurate model. Adding knowledge of the total surrounding establishments to a grid, increased the ROC AUC by almost 4 percent on the initial trials. Temporal features (such as time of day, month, year, etc.) also play an important role. Without the inclusion of rich temporal features the system learns the spatial distribution of crime, but is unable to distinguish the time of the day in which a crime will happen.

When we evaluate the system with a more imbalanced version (closer to reality), this problem becomes more apparent. The effects of undersampling uniformly are discussed by Liu [27], showing how different classifiers and sampling strategies affect the predictive power of a model. Our results align with the findings of this study, showing an unchanged recall but a sudden drop in precision. That is, more safe zones are being misclassified as dangerous. We hypothesize this happens for two related reasons. First, under-sampling biases the model towards a higher number of positives than are truly represented in the real dataset. Second, the lack of fine grained temporal features makes the system incapable of determining ”when” a grid is dangerous across the day.

We drive this hypothesis based on the observations of how the system behaves at even finer temporal granularity. Originally, the system was trained to predict crimes hourly. The system performed similarly when tested against a balanced dataset. However, when evaluated on the severely imbalanced dataset, precision dropped even more radically, while recall remained the same. The lack of rich temporal features in our dataset accounts for this loss of precision, caused by the inability to disambiguate within grids across time as efficiently as required by the level of detail provided by the temporal window. It is important to note that despite the imbalance, the minority class is effectively discriminated and unaffected by it. This trade-off between precision and accuracy is explored in detail in the following sections.

Given most research focuses on hotspot detection, i.e. determining whether a particular area will have relatively more crime in the future, a comparison with results of existing work might prove confusing. Bogomolov[7] et al. achieves an F1 measure of 67.23, which is comparable to our results of 67.63 percent on the balanced dataset. Our trials on imbalanced data show an fmeasure of 49.01, but preliminary testing shows this can be improved by training on a truer version of the dataset. It is also important to note that their classification task is at the granularity of months, whereas we are predicting at the granularity of hours, a significantly more difficult task. Nevertheless, our results are comparable with their findings.

IX. KYA: Know Your Area Application

In this section, we present a possible structure for a mobile platform that leverages the capabilities of our back-end to provide just-in-time information about a locality to a user on the go. First, we recognize an inherent problem with technologies available for crime mapping, and a possible reason why such technologies haven't been adopted to the prime of their capabilities. If Crime Mapping applications are available to the public, presenting zones that can potentially be more dangerous that others, why are these applications not widely adopted by the public?

Hot Spot theory suggests that knowledgeable individuals can avoid certain locations likely to be stalked by criminals [8], thus avoiding danger more efficiently. However, no mechanism exists to acquire the necessary knowledge to do so without proactively researching an area. That is, an individual must preemptively create a route using the mapping application, effectively increasing the cognitive load on the user. In essence, instead of enjoying the commute, people need to inspect the area they will traverse, making assumptions of what is the safest route, and somehow record what the intended trajectory will be. The task becomes more complicated when the temporal component of crime is present and what holds true for the moment of planning might not accurately represent the safety of a place at the moment of traversal. Instead, We envision a mechanism that allows users to preemptively avoid exposing themselves to crimes of place through reactive measures, with no need of a priori knowledge.

The trained regression model can be employed to predict the expected number of crimes for the area of interest. These expected probabilities can be stored along with the grids in the Mongo database, and updated quarter-daily as required. To further simplify the metric in relation to each grid, a linear quantile mapping can be used to represent the danger of an area relative to the whole grid, assigning levels from 1 to 10. In this form, an area of level 1 represents a relatively safe area, where less crime is expected in relation to the rest of the grids for a particular quarter-daily forecast. Both the regression metric and the relative classification would be stored in the geoJSON.

A front-end application can be installed in the user's phone or wearable device of choice (e.g. Android smartwatch).Through transition based geofencing [4], the system can notify users when the condition of mobility in the direction of increasing danger is met. By combining these components with the affordances granted by wearable devices, such as an Android watch, we can seamlessly notify the user of danger.

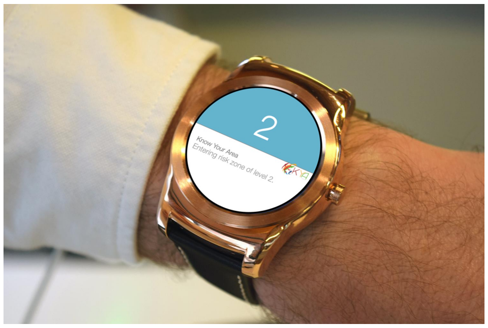

Fig. 6. A wandering user can be notified by the system when he/she enters a zone of risk that is higher than the one they previously traversed in.

With the envisioned system, the user is capable of wandering freely without prior knowledge about an area. Whenever the user wanders or is about to wander into an area where the "risk level" is higher in comparison to the area where they previously were, the mobile device can notify with a simple push notification, allowing the user to take an informed decision about whether to continue on the path or retroactively change their trajectory to avoid danger. The application could show the user's current location within the grids on a map interface, allowing for easier navigation or circumvention of dangerous zones.

In the case where the user wants to plot the safest route to a particular destination, the system could find the best compromise between safety and convenience by performing a modified version of the shortest path algorithm on the grids, using the expected number of crimes for each grid as the cost/weight of traversal through that particular grid. The application could then provide step by step instructions using the Google Maps API to guide the user to the destination traversing the shortest-safest path to it.

X. WEB APPLICATION

In order to present the application graphically, a web interface was implemented using HTML 5 and CSS. The dashboard makes use of the Google Maps API to present a mapping layer that shows the area under study. The classifications of an area are stored within the GeoJSON grid in a remote Mongo database. In order to keep the application responsive, the system does not load all the grid at the same time. Instead it presents a certain number of grids depending on the zoom level. Three zoom levels are supported, of which two level present arbitrary grids on top of the area of study and the third level shows the actual grids contained in the Mongo database. For the purpose of the project, the dashboard presents the map of NYC with the prediction results displayed over each grid. All the grids in green represent true negatives (no crime predicted). Conversely, the red grids represent true positives (crime predicted). Areas in orange represent places where crime happened but was not detected (false negative). And areas in blue show places where crime was wrongly predicted (false positive). The application can be accessed at kya.media.mit.edu.

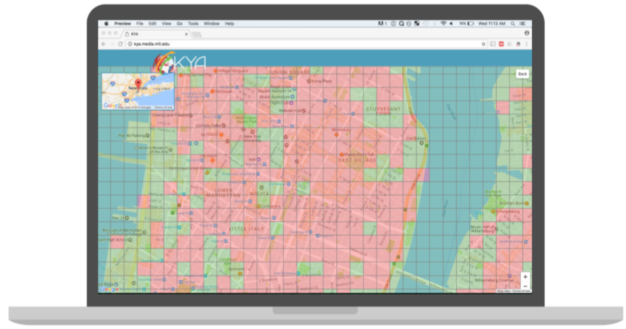

Fig. 7. The web application dashboard allows the visualization of the actual and predicted robberies over the city of New York.

XI. SOCIAL CONSIDERATIONS

Previous sections presented a machine learning system that provides crime forecasts to the general public. As discussed earlier, this system could become the back-end for a mobile application that informs users in real-time where and when a crime would occur. In this section, the socioeconomic implications of such a platform will be discussed in depth. For the purpose of this discussion, we consider a scenario in which the platform has been widely adopted by the public.

First, we focus on the precision-recall tradeoffs in crime prediction and the cost of optimizing for one or the other. We explore the implications of bias in the data that may affect what the system reports and how people interpret this information. We delve deeper into impact on topics including segregation, stigmatization, tourism, and, housing. Beyond these topics, this section will also examine the way the proposed system could be exploited and the social implications such exploitations could entail.

A. *Precision vs Recall*

Within the context of this work, precision refers to the ability to correctly classify a crime as occurring in a grid. That is, the capacity to which a prediction is correct. Recall refers to the ability of the trained model to detect relevant entries, which in this case constitutes identifying instances of criminal activity.

When determining which objective to optimize for, it is crucial to think about the cost of the systems mistakes. For instance, if the model was optimized for precision, then it would correctly classify areas, at the cost of being able to detect criminal activity. In this case, the cost of failing to detect that a crime would happen can potentially impact the wellbeing of a human. Conversely, optimizing for recall would greatly improve the chances of identifying the dangerous areas at the cost of misclassifying safe places as dangerous.

The dilemma lies in which type of mistake results in a higher loss. Is it better to tell people that a place is dangerous when it is not? Or is it better to tell them it is safe when it might be dangerous? Intuitively, we might be misled to think that the cost of putting a human life in risk is much higher. That is, it is better to say that a place is dangerous when it is not—so long as we ensure the safety of the user. However, the cost of skewing human perception can have a high impact when observed from the macroscopic perspective of society as a whole.

Consider the case where the application has been widely adopted. In this scenario, a majority of people use crime prediction to plan out their daily commute and activities. If the model was optimized for recall, at the cost of precision, the number of grids classified as dangerous would be higher than the number of grids that actually are. As a result, human mobility and perception could be greatly affected assuming the users trust the application more than the mental model theyve built about the locality. Essentially, a shift in human perception regarding the safety of a place can negatively impact its economy, especially if there is a sustained level of less traffic and avoidance. We discuss this further in the following sections, underlining the dangers of playing with human perception without sensible considerations about the possibility of perpetuating segregation and stigmatization of areas misclassified as dangerous.

Alternatively, if the model is optimized for precision, then areas that are dangerous might not be detected. This could result in people believing an area is safe when it is actually dangerous. Such a system could increase the potential or opportunity for crime to occur—assuming that users might let their guards down or be less attentive due to a misguided trust on the application.

We take no strong stances regarding which parameter to optimize for. Instead, we propose that the solution to both problems presented in this discussion is complete transparency about the decision process. Neural Networks are a black box, and understanding the processes by which a place was classified dangerous or safe is beyond the capabilities of the state of the art. However, the system could be transparent about the design choices that were made through the modeling process. This transparency allows users to make informed assumptions of what the systems prediction means in terms of reality, instead of misconstruing the predictive ability of the model as ground truth. As a result, a place misclassified as dangerous might not necessarily be perceived as truthfully so, precluding the possibility of stigmatization. Conversely, a place misclassified as safe wouldnt influence a user to lower his/her guard while traversing the locality.

B. User Profiles

In this section we consider the different profiles of people who might use the platform and how it can potentially influence the mobility landscape of a city. In order to delineate the discussion of socio economic impact in the following sections, it is important to understand who the users of an application might be, and how they potentially use the platform. To characterize these user profiles, we identify three key features that enable a discussion regarding the way the application might be used: first-hand knowledge of the area, aversion to risk, and the capacity to which a user trusts the predictive platform (predictive trust).

For the sake of this discussion, we present three possible profiles that could result from different combinations of these key characteristics:

- Locals: High spatial knowledge of the area, variable aversion to risk, with a relatively lower predictive trust.
- Newcomers: Low spatial knowledge of the area that evolves over time, aversion to risk, and varying degrees of predictive trust.
- Tourists: Very low spatial knowledge of an area, mid to high aversion to risk, and varying degrees of predictive trust.

Locals have lived in an area for a relatively long time. As a result, they usually have a greater spatial knowledge of the place. The knowledge they have acquired about a locality over time, allows locals to create mental models about the relative safety of the city at different granularities (e.g. neighborhoods). These mental models are likely the result of first-hand experiences, and the diffused opinions theyve come across in their social interactions. Local media is a likely source that shapes this mental model. Given this tried and tested model of perceived safety, locals might not be as inclined to use this platform, as their predictive trust is biased by their knowledge of the area. They may also belong to an older demographic, and may not willingly trust the platform or adopt technology into their daily life. The cases in which they may use the platform include travel to areas where they could be categorized as Newcomers or Tourists. They may also use the platform when they are moving in a part of the city they are not familiar with.

Newcomers are users who have recently moved to a new place. For instance, they might be students moving abroad or workers relocating to a new city. Newcomers start off with low spatial knowledge, which increases as they acclimate to the new area. Initially, they might be inclined to adopt the platform as a means to safely explore their environment. As they do, they also start creating a mental model of perceived safety similar to that of a Local. However, this mental model is highly influenced by the predictions presented by the system. Initially, a Newcomers trust on the platform stems from a combination of their lack of spatial knowledge and their innate aversion to risk, which varies according to age and personality. Eventually, a Newcomer grows less reliant on the platform and transitions into the role of a Local.

Tourists are users who are exploring a new area without intent on remaining for an extended period of time. This could be people vacationing or merely visiting an area for a short period (e.g. business trip). Tourists generally have low spatial knowledge of an area which, unlike for Newcomers, does not evolve over time given the short period of visit. Aversion to risk in tourists is relatively higher than for other profiles, due to fear of being involved in a dangerous situation away from home and their support groups. This holds particularly true for international tourists, whose culture and language might mismatch significantly with those of the locality they visit. It is easy to imagine tourists adopting the platform to navigate through a foreign city, state, or country, figuring out where to stay, where to go, and which paths to take.

We hypothesize that Locals, who constitute the majority of a places population, are unlikely to adopt the platform in sufficient scale to shift the mobility patterns of a city drastically. As so, the societal impact on a particular area is not likely immediate in this sense. However, cities which see a constant influx and outflux of people (e.g. Boston) can potentially be affected over time. Since a Newcomers perceptions of a place is more malleable that those of Locals, they represent a population that is particularly susceptible to perceptual bias about the safety of a place. This perceptual elasticity can be dangerous in perpetuating shifts in mobility patterns about a city or region. In a sense, a Newcomers reliance on the application decreases as the predictive model becomes embedded in their mental analogue. As a result, the perceptual landscape of a city can change over time as biased Newcomers transition into the roles of Locals.

Tourists don't suffer from the perceptual elasticity of Newcomers, mostly because they don't reside in an area long enough to create a mental model of safety. However, tourist driven economies can be both positively and negatively impacted by the adoption of a crime predictive platform. These effects are discussed thoroughly in the following sections.

C. Bias in the Data

In this section, we examine the possibility of bias within our criminal incident dataset and its potential impact within society. One of the biggest issues our platform has to grapple with is unreported crime: the model is getting an incomplete picture of the types and frequency of crimes that occur throughout the area of study. Statistics show that around 52% of all violent victimizations were unreported in cities across the US. from the time between 2006 to 2010 [30]. The model presented in this work targeted robberies in New York City, which coincidentally are among the crimes that are typically unreported. According to the Bureau of Justice Statistics (BJS), from 2006 to 2010, the highest percentage of unreported crime included household theft at 67% [30]. Additionally, about 41% of robberies were not reported around the US in that same time period [30]. The reasons for not reporting the crime included: the victim feeling the police would not or could not help, the crime not being important enough for the victim to report, or the victim fearing reprisal[30].

As mentioned earlier, one of the main reasons crimes go unreported is because the victim feels the police would not or could not help[30]. This implies an inherent distrust in the police and law enforcement system[30] that results in the model receiving only the information that the public feels safe reporting to the police. Having a model that is getting an inaccurate and "censored" view of the true crime that occurs is inherently dangerous. People will grow to trust a system that is only presenting a fraction of the real danger. In reality, we may be getting high recall for the crimes that we are aware of, while missing a significant portion of robberies.

Given the alarming number of crimes that go unreported, we can assume the model has a skewed or biased view of the world based on the crimes that actually are. Intuitively, this means that our system might not be able to fully understand how crime occurs across the city, which results in faulty predictions. At first glance, it might not be apparent that the reporting problem goes beyond hindering the capabilities of the system to predict crime accurately.

Statistics show that although African Americans compose 12% of the population, they amount for 47% of arrests and reported felonies[31]. Studies have shown that bias in policing is responsible for this. In essence, bias results in increased supervision or sensibility toward certain demographics. In fact, studies suggest that one-third of African American males aged 2029 are under the supervision of the criminal justice system on any given day[32]. As a result, police reports often include incidents of particular racial groups more disproportionately than others. This represents a substantial problem for crime predictive technologies, given the model learns from the spatial properties of where crime is reported. Although the location doesnt directly map to the sensitive variable (which in this case has proven to be race), the census demographic data can indirectly represent this skew. Consequently, our predictive model could be learning that places with particular concentrations of racial profiles are to be classified as dangerous.

It is important to consider how these 'hidden feedback' loops can perpetuate segregation of certain communities. For instance, suppose that bias accounts for the police allocating a higher number of officers to a certain neighborhood. As a result, more criminal activity is reported in this neighborhood relative to others in the area of study—given the police is actually there to witness the incidents and intervene. Because the predictive system is trained on these incomplete set of incidents reports that register a higher frequency in this neighborhood, the model becomes biased towards the particular area. Worse, if this happens across multiple neighborhoods that share similar demographic distributions, the model could generalize erroneous and racist conclusions about where crime will happen. Assuming the police takes advantage of the predictive models to manage their resources more effectively, they might decide to allocate even more police officers to the denoted areas, resulting in a feedback loop that perpetuates discrimination. We delve deeper into the topic of discrimination in the following sections.

A way to gather more accurate information about all the crime that occurs in an area is to pair our system with a crowdsourced crime reporting mechanism. Our platform could build trust in its service by allowing users to report crime when it occurs. This way the criminal incidents that are used to train and update the model are democratized in a sense, allowing for a truer representation of the criminal landscape of an area. As more people participate in reporting crimes that typically remain unreported, the model would benefit from the increase in information, citizens would benefit from a system that is more robust in its crime prediction, and communities would also benefit from a system that is transparent and open about the information it uses to predict crime. We acknowledge that a crowdsourcing platform entails a plethora of additional issues including an increased complexity in the system, the requirement of a critical mass of active users to accurately combat skewed views of the world, and the difficult task of filtering entries to the system to exclude garbage or spam. Nevertheless, a crowdsourcing approach could help mitigate the impact of underreporting and bias that would otherwise be prominent in the available raw data sets.

D. Social

In this section, we consider how use of the platform may result in segregation and promote stigmatization of areas classified as dangerous. We close with a discussion on how crime predictive technology has the opportunity to align the perception of its users for better or worse.

Although segregation in a formal sense of the word has been banned in the US, neighborhoods do tend to self-segregate: some areas are much safer than others, and these tend to be occupied by households that are predominantly white"[43]. Poor African Americans and Hispanics are more likely to live in neighborhoods of concentrated poverty[49] whereas poor whites will likely live in areas where most people are not poor[44]. Interestingly African Americans, regardless of income level, are rather segregated from whites[44]. In general though, African Americans of any individual economic standing will generally live in a neighborhood that is worse than that of whites who are in the same economic standing[44]. Whites tend to self-segregate, and there is an unwillingness of white Americans to live in areas that have a high percentage of African Americans[45].

Racial segregation in American cities occurs for reasoning beyond just income or wealth[43]. The segregation could be attributed to reasons such as racial steering by real-estate brokers or redlining by mortgage lenders[43]. According to the research conducted in this paper, migration to safe locations and safe neighborhoods occurs at higher rates for whites compared to blacks, and that is one of the reasons behind racial segregation beyond income[43]. If this is the case, then it is plausible that our platform could be used by residents or people in the housing market looking for areas to move to.

Beyond people who are actively looking, our platform could also be used by people who are willing to move to a better, safer place that has more opportunities. Based on previous research, people who are a part of a higher economic class and people who might identify themselves as Caucasians might disproportionately move to areas that are distinctly marked as safe. The flow of people who belong to higher economic classes to places that are safe will leave behind weakened areas. People who are in a lower economic class and have less resources and opportunities available will be the ones left behind. This type of migration, which causes segregation, can also lead to a downward spiral of the state of the segregated, dangerous area[46]. Moreover, because of the aforementioned hidden feedback loops and bias in the data used to train the predictive model, the impact can be potentially higher for some racial groups more than others. Our platform has the potential to encourage people to move and migrate to safer areas, thus increasing the chance for self-segregation.

In states and cities across the United States, there is a certain level of stigma attached to people living in places that are considered unsafe. People who are a part of a lower socioeconomic class are among a majority of people living in those areas[43], for reasons that could include the affordability of those areas. Where a person lives can impact their quality of life and the opportunities they have[47]. Where a person lives can also impact their mental health and their own perception of themselves[47]. The perceived safety and quality of a neighborhood, therefore, impacts the mental state of a person living in that neighborhood[48]. It has been proven that the type of community can really impact mental well-being[47], and often, people who are living in neighborhoods where they feel they are unsafe are more likely to feel depressed, anxious, and isolated.

When people feel high levels of trust, social support, and empowerment in a neighborhood, they report lower levels of psychological stress[48]. People will inherently have their own biases towards a place and residents of the area, and will even have their biases about the level of wealth and resources in certain localities. But for the most part, those biases will be based on peoples own perception of an area and personal exposure to it through stories, articles, or word of mouth. With our model, peoples biases might be formalized, validated, and proven, thus increasing the chance for more stigma to be associated with a negatively classified place.

As discussed in previous sections of this work, in many cases, peoples inherent perception of a place may not actually correlate with how safe or dangerous a place really is. This biased, incorrect perception of a place could negatively impact the way people interact with it. People who have a negative perception of a safe place may never consider living there. Safe places may go uninhabited and underused. Perhaps this model could be used as a trainer to help nudge peoples perception of an area into a right or accurate understanding of grounded safety. In this way, safe places that are thought of as dangerous could see a greater influx of people. These places could benefit from more traffic. Alternatively, in the case where people think a place is safe when it is actually dangerous, the model could correct a persons perception and potentially save or prevent a person from being victimized.

The model would be helping people understand which places are truly dangerous and which places are truly safe by aligning their perception with reality. If our model is inaccurate and places that are dangerous are classified as safe or vice versa, then peoples perception is misaligned with reality, and aligned with the bias contained within model. As mentioned earlier, in the section discussing precision and recall, an incorrect perception of the danger of a place due to an improper classification could have negative consequences. People would be more at risk to discriminate against a place, thus impacting the economy of that place. Or, people would be more at risk to find themselves in a dangerous area, under the wrong impression that it is safe. Perception alignment could be a powerful aspect of the tool regardless of which way the tool alters peoples perception of safety.

E. Economic

The proposed platform offers users a more holistic picture regarding the perils of an area, potentially building the trustworthiness of a place and enhancing the perception of people towards it. In some countries, the tourism industry plays a significant role in the economy. These 'tourist driven' economies benefit from the influx of capital and profit on taxation directly associated to tourism to bolster their economic growth. The profitability of taxation directly associated to tourism (e.g. $100 billion in 2013 for US market) is dependent on the countrys brand value[1]. A study on the economy of New Orleans concluded that the proactive involvement in safeguarding tourists can increase the citys brand value, thus increasing profitability[35]. Conversely, if an area is perceived as dangerous, the tourism industry is directly affected, consequently disrupting the economy of a country. Take for instance Egypt, where the tourism industry was 13% of GDP as of 2010 and employed an estimate of one out of seven workers. When the Arab Spring occurred, the number of tourists that visited the area dropped from 14 to 9.5 million, greatly hindering the economy[34]. Thus, the perception of safety plays an important role for the tourism industry and economic growth of tourist driven economies.

Areas that are notorious for crime find that many of their tourists are driven away. Being linked with crime in the media also has a negative effect on the economy of these places. According to[40], the media tends to overemphasize the negative incidents that happen to tourists. In other words, a small number of incidents can have a significant impact on the perception of a touristic spot.

As discussed in the user profile section of this work, tourists are more likely to adopt crime predictive technologies. If the platform works effectively during a tourists visit, they should enter and leave an area with a positive impression. By helping tourists to stay away from areas where they can become the victims of crime, the proposed system can reduce the impact of crime on tourist influx and in turn benefit the economy of a place.

Housing prices will generally be impacted negatively if an area is considered to be dangerous, unsafe, or of lower living quality. As some researchers have observed: a high crime rate is strongly and negatively associated with neighborhood quality, having a marked impact on the prices homebuyers are willing to pay for a house[38]. According to this same paper, as crime is perceived as detrimental, individuals may be discouraged from buying a house and this behavior is, in turn, reflected in the market property price[38]. This has been the case historically. In a report examining the effect of crime in 1978, researchers found that one standard deviation increase in the crime rate resulted in a 3% reduction of the houses price[37]. This trend is true across different cities, states, and countries. Homes have been found to be highly discounted in Jacksonville, Florida in areas that have high crime[36]. In the city of Barcelona, even in districts that are merely perceived as less safe, houses are highly discounted: on average valued 1.27% lower[38]. This relates to the previous discussion on perception alignment and its potential impact on the socioeconomic landscape of a city.

Crime Prediction technology could impact housing prices in two ways. A positive impact can be achieved by correcting the perception about an area that is erroneously thought of as dangerous, thus increasing the property prices to a fairer value. On the contrary, places incorrectly labeled as dangerous by the system could suffer a reduction in value as prescribed by historical trends regarding prices of places that are thought of as dangerous.

Small businesses and establishments have been shown to be disrupted negatively due to violence and crime[39]. Surges in violent crime hurt establishments more in areas that typically have lower levels of crime[39]. The increase of violent crime in areas that are already known for having higher levels of crime has no significant effect on local business growth[39]. On the other hand, cities in which violent crime increased dramatically in low crime zones saw a greater reduction in the growth rate of new retail and service businesses, and employment in existing businesses[39]. Businesses such as grocery stores, doctors offices, and barber shops are among the ones most impacted by increases in violent crime[39].

In general, when crime occurs in areas that are known for having lower levels of crime, establishments can close and people can lose their jobs[41]. In areas that are used to higher levels of crime, lower employment rates and fewer new business are common. Additionally, crimes against small businesses, like shoplifting and theft, tend to go unreported[42]. The impact on small businesses lasts beyond just the crime itself: businesses that are victimized might increase prices on their items to compensate for losses. Employees might be worried that they may be laid off and some businesses may be forced to close[41]. For shop owners and establishment owners, crime impacts psychologically and economically.

For shops that might already be struggling with crime, a system such as the one presented in this work in which people will clearly know what areas are safe and what areas are not, could harm not only the establishment owners but also the customers and consumers. Furthermore, if predictions misclassify as dangerous (false positive), establishments in safe localities might suffer from lower traffic and revenue unfairly. Establishment owners might increase their prices as a way to combat against less inventory and customers. Owners might also opt to hire less people or lay off more of their employees if they are not getting enough revenue. Under extreme circumstances, owners might even decide to close their shops.

If our system is widespread and people are highly aware of which areas are unsafe, they might also avoid establishments they previously frequented. Less customers would correlate to less revenue, thus forcing establishments to choose between increasing prices, closing, or hiring less people: all of these options negatively impact the economy of an area. People who merely go to an area to buy something at an establishment can always choose to go to another locality. However, people living in that area might have to deal with higher prices or might even have less access to regular stores as more and more small establishments are forced to close.

F. Exploitation

The discussion presented in this work has been based on the assumption that the platform has been widely adopted by a significant amount of users. As so, it is important to recognize the possibility of the system being exploited by different parties and how that could result in negative impact on the socioeconomic spectrum of an area. We focus on two different parties that could take advantage of the system: criminals and system administrators.

To an extent, it is not hard to believe criminals would take advantage of the predictive platform to target individuals more effectively. Several reports of criminals using social networks to carry out crime and select their victims have surfaced following the wide adoption of these technologies. For instance, there have been reports of criminals determining when people are on vacation based on Facebook posts to target their houses for burglary[33]. Furthermore, criminals have used social networks to target law-enforcement entities by leveraging geo-tagging to track down people. Even if the model was not widely adopted, because it is open access, anyone would have the ability to see the visualization and prediction of danger about an area. Criminals could monitor the app as a mean to change their behaviors and target zones that are denoted as safe by the system, under the impression that trustworthy users of the application might lower their guard or be unprepared for assault. Criminals could assume that people using the platform will change their mobility or leisure patterns in a way that reflects the prediction mapping. As a result, they could repurpose the platform as a tool that can help them stalk potential victims or help them plan their next strike.

In order to thwart criminal exploitation of the system, the platform could adopt a policy of security by obscurity. Instead of making the whole predictive landscape of a city available for users to explore freely, the system might only provide reactive notifications when a person is moving towards areas of danger. Similarly, the platform could focus on presenting the shortest safest path, without disclosing the actual predictions. Without this knowledge, criminals cant use the mapping application to track down unsuspecting users without significant effort.

We previously discussed how crime predictive technologies can pose significant impact on local establishments by shifting human mobility away or towards a business located within the area of coverage. We further anticipate the ability for businesses to exploit the system to attract customers by false claims of safety. If the platform administrators are not regulated, they might be coerced or influenced into altering the corresponding levels of safety. One could imagine a scenario where safety becomes a brand easily attainable by well placed bribes. Although this poses a problem beyond the scope of crime modeling, it is relevant to open discourse of how systems that operate so influentially in society should be regulated to avoid exploitation of its users.

XII. SIMULATION FRAMEWORK

Although developing a framework to validate the assumptions presented in the Social considerations section of this paper is beyond the scope of this work, we present a possible solution for future studies of crime prediction impact on the general public.

A. Routine Activity Theory

Criminal Opportunity Theory (COT) posits that offenders make rational decisions about choosing the most suitable victims/targets that require the least effort and present the most reward [28]. Routine Activity Theory (RAT), a subset of COT, further suggests that in order for a crime to occur there must be three components: a suitable victim, an offender, and absence of a capable guardian. In other words, narrowed down to criminal activities such as robberies, this theory suggests that criminals actively look for victims that are not surrounded by a possible guardian. A possible guardian is often interpreted as law enforcement personnel, but it may be the case were a multitude of individuals could be considered as guardians to some extent. I.e. crowded places are more likely to be safer for a possible victim. Routine Activity Theory implicitly suggests that individuals have the choice to actively become victims by placing themselves in locales or situations where it is more likely that crime will be committed against them[29].

Fig. 8. According to RAT, crime occurs when victims and offender coalesce in space and time where a guardian is not available.

B. Simulating Crime

With Routine Activity Theory as a platform, a grid simulation can be performed to observe the effect of how crime prediction technologies can impact several aspects of society. The system would create an arbitrary n x m grid. This grid represents the area under study (e.g. New York City), where each sub-grid represents a particular section of the area (e.g. 23 squared kilometers). Three different agents can populate this grid: potential victims, offenders/criminals, and law enforcement entities. The behavior of each agent can be embedded as a series of stochastic processes whose variables can be tuned to more accurately represent the actual behavior of these agents in the real world. For the simplicity of these discussion we posit example strategies that each agent could follow:

- Criminals: Avoid law-enforcement personnel and stalk nearby grids where multiple possible targets coalesce.
- Law Enforcement: Monitor certain sectors as dictated by a global policing strategy, allocating resources to places that meet certain characteristics.
- Possible Victims: Move freely throughout the grid in temporal patterns that could represent daily commute to work, home, or recreational exploration of the city.

These strategies are by no mean exhaustive and only represent a naive example to illustrate the different behaviors that could be modeled to make the simulations reflect reality for the study. More accurate and empirically proved mobility patterns can be used to express the behavior of criminal agents and policing resources. It is important to note that any results driven from these simulations are only as accurate as the capacity of the modeling techniques to accurately portray the mobility patterns of the three agents across space and time.

Parting from the triangle Routine Activity Theory proposes as a model to explain criminal incidents, we can create an instance of crime each time a victim agent intersects with a criminal agent and there is no law enforcement agents in a nearby grid radius. Similarly, if there is a certain density of possible victims within the grid when the criminal agent intersects, a crime might or might not happen, depending on stochastic behavior modeled for the criminal proneness to risk for the simulation parameters. This modeling would allow us to observe how the criminal landscape of the city behaves over a particular window of time.

C. Simulating Predictive Technologies Available to the Public

To understand the possible impact of predictive technologies available to the general public, we can extend the simulation paradigm presented in the previous section to imbue possible victim agents with a certain degree of knowledge of the criminal landscape. In other words, a grid mask overlay on the area of study can mark grids that designate with some probability the tendency of criminal agents to stalk these areas to commit crime. This would cause an effect on the possible victims mobility based on the victims profile. The victims profile can model the propensity of the victim agent to take risk (risk-aversion metrics taken from psychology) and the willingness to trust the application's predictions. Additionally, the number of possible victims that adopt the usage of the application should be adjustable. This would allow to observer how the landscape of crime changes as the adoption of the application becomes widespread.

Our hypothesis is that the application will be useful in reducing the amount of criminal encounters for active users, so long as the critical mass of users does not exceed a certain threshold. If the total number of adopting users does not exceed this threshold, the mobility density remains relatively unaffected by the application. As so, criminals will continue to stalk the same areas, and the system's predictions would hold accurate for longer windows of time. However, if the application is adopted by a percentage of the population that exceeds the operational threshold, the mobility patterns will be affected drastically, effectively changing the density of the populace at distinct grids. In consequence, the criminal agents will most likely alter their mobility patterns to adjust for this shift, and the application's accuracy for short windows of time will be poor.

D. Multiple Victim Profiles

As discussed in the social implications section of this work, the impact of predictive crime technologies for the public is very dependent on the users that adopt the system. In the simulation, this adoption behavior should be modeled accurately to better understand the effects of the technology in a broader sense. The possible victim profile would model factors such as:

- Risk Aversion
- First-Hand Knowledge of the Area
- Trust on the Application

For instance, risk aversion could model the probability that a possible victim will ignore the application's suggestion of danger regardless of the agent's belief in the application. Several demographics can be more or less risk averse, and the census data of the population could shed some light as to how the overall modeling of the agents could be distributed for this factor. First-Hand Knowledge of the Area refers to the experience a person has acquired about a certain locality. Our hypothesis is that people with first-hand knowledge or experience of an area should be less reliant of the predictive application, placing more trust on the collective experiences that they have acquired about a locality, and thus rarely following the directives of the application. Finally, the trust on the application models the agents beliefs regarding the predictive power of the application. These three metrics are examples of factors that could help model different kind of users, and the impact of the application on their mobility patterns.

For instance, locals of an area have a high degree of first-hand knowledge of the area, meaning that they might ignore the application's predictions unless they move in a part of the city where they don't usually traverse. On the contrary, tourists can be modeled as having little knowledge of the area, and higher risk averse. For the purpose of the simulation, this victim profile suggests a tendency to avoid dangerous grids when traversing the region.

E. Economic Impact on Vendors

In our social discussion we addressed the possible implications that crime prediction could have on the economy of a place. The proposed simulation framework could allow for the exploration of this topic by adding additional vendor entities on the grid. Vendor entities can be statically placed throughout the grid. Whenever an agent enters a grid with a vendor entity, a possible sale is registered. Different scenarios could be observed such as vendors within areas denoted as dangerous or vendors in safe areas surrounded by dangerous areas. We hypothesized in our previous discussions that vendors can be affected by a change in mobility. However, the degree to which such a change would affect highly depends on the amount of adopting agents, the various victim profiles, and agent intent.

F. Predatory Behavior Paradox

Given the predictive application would be available to the general public, and there is no means to discriminate between possible victims and criminals, it would be ideal to model the scenario where the criminals have access to the same predictive technology. Consequently, a criminal agent can take advantage of this knowledge to shift its mobility to stalk areas that are classified as "safe" by the system (see section X of social discussion). We can model this behavior in the simulation framework by making the predictive grid available to both possible victim agents and criminal agents. The criminal agents could then shift their mobility patterns to take advantage of this knowledge as defined by a highly predatory strategy. The number of criminal agents that take advantage of this knowledge should be adjustable, to observe how the criminal landscape behaves.

We hypothesize that an increased adoption among criminal agents of this technology could create scenarios where those who trust the application would be more prone to becoming victims of crime. However, we anticipate a more cyclic behavior, where the trust on the application is consequentially decreased every time a person becomes the victim of a crime while following the application's directions. As so, less people would use the application and criminal agents would find less benefit in exploiting the application's predictive power. This hidden feedback loop can be further explored using the simulation under different set of parameters.

XIII. CONCLUSION

In this work, we explored the capabilities of Neural Networks for predicting crime. More specifically, we trained both binary classification and regression models to identify when and where robberies would occur in the city of New York. We leveraged information about criminal incidents, weather, census, and Google Places data to use as features to enhance the predictive capabilities of our model in quarter-daily temporal windows. The implemented system was evaluated using ten-fold and Leave One Out (LOO) cross validation techniques for the within-year and across-year scenarios respectively. Precision, Recall, F-Measure, and AUC were selected as the metrics to present the quality of the predictions of the implemented model, due to severe class imbalance in our dataset. The system showed roughly 67% precision and recall, and an AUC of 87%. The results were compared to findings in similar works, showing comparable accuracy despite the finer temporal windows. A sharp loss in precision was observed when testing against a more imbalanced version of the dataset, showing how undersampling biased our model towards the minority class. We presented a plausible platform that could leverage the predictive capabilities of our model to provide just-in-time information to wandering users in order to avoid crime. Furthermore, a web interface was developed that allows the visualization of our model's prediction overlayed on top of an interactive map of the city of New York.

We finalized the socioeconomic section by proposing a simulation framework based on Routine Activity Theory that could be implemented to further test the assumptions presented in the discussion.

XIV. FUTURE WORK

Crime predictive technologies for the public show promise to help users avoid dangerous crimes. However, as presented in this work, many considerations (social and technical alike) have to be explored in order to develop sensible solutions to these problems. There are several avenues for continuing work on this topic, some which were slightly outlined as potential frameworks to asses many of our assumptions. We divide this section in two sections, discussing the possibility of future research in both the technical and the social spectrum.

A. Technical Components

This work presented results for models trained on undersampled datasets. In order to obtain a more significant measure of accuracy of the developed system, a model should be trained with the full dataset. Given our storage and computational capabilities, this was not possible for the scope of this project. However, we did perform evaluations on a severely imbalanced set, albeit not the full dataset.

The exploration of additional features is due to improve the accuracy of the system. We believe more temporal features(i.e. features that change over time) is required to achieve prediction at a finer granularity. These temporal features allow the system to distinguish better between zones were robberies have been committed. Potential candidates are more weather features, human mobility over a particular grid at a finer granularity, social media cues (e.g. tweets or events), and media sentiment.

In this work, we presented a mechanism to take advantage of the models trained for crime prediction. We believe implementing this platform would be useful for two reasons. First, crime prediction can be tested in the real world with real people, allowing for a better understanding of the best method to influence user mobility. Second, given the plurality of sensors already available on mobile devices, the application could help track the user's mobility after a notification (using GPS) and biofeedback (e.g. heart rate), in order to determine if the notification of risk (1) is effective in modifying a user's commute and (2) has any negative impact on the user's psyche.

Finally, the area of crowd-sourcing was not addressed in this work. We believe a well established crowd-sourced feedback for predictive crime models would mitigate the problem regarding the fact that not all crime is reported by the police, which results in an incomplete view of the world.

B. Social Components

A better understanding and exploration of bias within the data used to train crime predictive models would allow for a more nuanced understanding of how it could affect demographics disproportionately. This is particularly relevant given the discussed reporting problems and the hidden feedback loops discussed in this work. Primarily, implementing the simulation framework described in the social section of this work, would allow for a better understanding of how the system could impact the social landscape of a city if it were widely adopted. Many of the views proposed in the social considerations in this work speculate the impact of the technologies. A formal simulation would allow the study of predictive crime technologies before deploying the aforementioned studies involving an actual front-end. The results from these simulations could be used to drive the discussion further.

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