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PREDICTING THE RISKS OF STREET VIOLENT CRIMES USING AGENT-BASED MODELING

Yifei Gong
Department of Computer Science
The Graduate Center, CUNY
New York, USA
ygong@gradcenter.cuny.edu

Feng Gu
Department of Computer Science
College of Staten Island
Staten Island, USA
feng.gu@csi.cuny.edu

Mengyan Dai
Department of Sociology and Criminal Justice
Old Dominion University
Norfolk, USA
mdai@odu.edu

***Abstract*—Criminological research has shown that most violent crimes are committed by a fraction of offenders, and a small number of geographic locations account for the majority of observed crime patterns. In policing, focused deterrence strategies are widely implemented to predict and prevent the crime occurrence. To facilitate these strategies, we develop an agent-based model to predict risky behaviors of police-focused high-risk individuals by capturing the complex dynamics generated by constant interactions within the autonomous agents themselves and between the agents and the environment. We incorporate both the criminological theories and the expert knowledge into the model and make full use of the public data, such as GIS data, census data, and official crime data. We use Hampton, VA, USA as an example to demonstrate that the model is able to predict high-risk individuals' likelihood of being involved in street violent crimes and their patterns. This study suggests the model has great potentials in improving the effectiveness of focused deterrence strategies.**

***Index Terms*—Crime risk prediction, agent-based modeling, person-based policing, focused deterrence**

I. INTRODUCTION

A comprehensive model that can incorporate various types of data and make accurate risk predictions has always been one of the most challenging endeavors pursued by criminologists and policing scholars. First of all, field experiments in criminal justice are expensive to carry out and difficult to develop [1], and, therefore, a predictive tool is desirable to help create an optimal experimental design based on crime patterns and the behavioral analysis. Moreover, due to the influences of many social factors and the limitation of policing resources, some field experiments are impossible to carry out, so a valid crime risk prediction model is a favorable solution to evaluate the effectiveness of a policy beforehand. A crime risk prediction model also serves as the central component of the person-based policing strategy, in which the police take prompt preventive actions upon selected high-risk individuals when their predicted risks of committing crimes are high.

Historically, criminological research has relied on statistical models for crime predictions. However, the drawbacks of statistical and machine learning models [2] have made some researchers gradually shift the methodology to agent-based modeling. These drawbacks include the failure to capture system complexity from real-world interactions and the simplification of spatial realism concerning how people travel. In contrast, object-oriented programming is the paradigm that lies at the heart of agent-based modeling, where entities like ordinary people are cast into autonomous agents like objects that can interact with other agents in the system and the environment. This bottom-up simulation approach can emulate large-scale social phenomena based on the agents' adaptive behaviors to provide an assessment of the effectiveness of crime control policies, such as focused deterrence strategies in policing.

In this work, we primarily focused on predicting the risks of high-risk individuals on committing street-level violent crimes (i.e., violent index crimes, such as robbery, forced rape, aggravated assault, and similar serious violent crimes). We do not consider domestic violence in the analysis because these two types of violence have different mechanisms and cannot be simulated in the same model. In this work, because we are aiming to provide a tool for the police focused deterrence strategy, we constantly evaluate the risks of high-risk individuals selected by the police department using its own protocol. Specifically, high-risk individuals are those meeting a series of criteria of risk factors known to the local police. We do not evaluate police officers' and common citizens' risks of committing crimes.

In general, we developed an integrative and comprehensive conceptual model based on various criminological and sociological theories and the expert knowledge. The related theoretical and empirical knowledge guides us to properly identify a wide range of important social and environmental factors for the criminal risk prediction. The developed agent-based model is a complex and GIS (geographic information system)-based large-scale model with 38 different risk factors from seven categories. It is able to simulate real cities with up to millions of agents in different categories, such as residents, high-risk individuals, and police. All agents are distributed in a real environment with GIS information, and the transportation system is integrated to generate real routings for

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the agents' movements. The model encompasses real data for accurate crime risk predictions, which include the census data to recreate a synthetic population, the environmental data to specify subareas in the city for different purposes, the patrol data to simulate the actual police patrolling activities, and the past crime data to identify crime hot-spots.

The rest of the paper is organized as follows. Section 2 reviews previous research on crime prediction models using agent-based modeling. Section 3 presents our model's detailed construction, including the environment, the agents, and the risk prediction method. Section 4 demonstrates a case study using our model in the city of Hampton, Virginia, USA. Section 5 discusses the results of the experiment and the corresponding analysis. Section 6 concludes the paper and discusses the directions of our future research.

II. Related Work

In recent years, many crime prediction models using agent-based modeling have been developed to examine specific policies' effects on crime rates, such as hot-spots policing. Different models are based on various criminology theories [3]. [2] developed a burglary prediction model to evaluate the effects of urban regeneration on the household burglary risk. They used the PECS framework [4] to provide the agents with motives for committing burglaries, and the opportunity theories [5]–[7] were also applied to let the agents make optimal decisions to explain why burglaries occur in different neighborhoods and help future urban developments. To expand upon the punishment element in the opportunity theories, [1] used the deterrence theory [8] to develop a robbery prediction model to test the effectiveness of different policing strategies. The significant deterrence impacts of hot-spots patrolling in the results demonstrated the importance of designing complex guardian agents with real policing activities since hot-spots patrolling is often adopted in real-life. Nevertheless, the expert knowledge of the police was not considered.

Researchers used different spatial representations to accommodate the varying landscapes of the modeling areas. [9] developed a burglary prediction model to replicate the spatial distributions of burglaries in Beijing. To capture the dynamics of the complex public transportation system in the local areas, they constructed the environment using the graph representation with nodes and paths, which is efficient in routing [10] and can analyze the relationship between accessibility and crime hot-spots at the node level. Another popular method to represent the environment is the grid cell. [11] created several virtual regions of the real cities using grid cells to evaluate the effectiveness of different combinations of policing strategies. The model incorporated the land-use data to assign different functional purposes to each cell so that the influences of crime attractors and crime generators were included. However, they didn't include the GIS information and the transportation of the environment for its more realistic representations.

It is very important to incorporate related real data in agent-based models for more accurate predictions. [12] illustrated the extensive usage of miscellaneous data including the past crime data, the environmental data, the transportation data, and the location-based social network data for simulating crimes. In their proposed agent-based modeling structure, these data were used for automatic calibration and the agents' behavior design. [13] demonstrated how to generalize crime patterns and conduct the victim analysis at the individual household level by integrating an agent-based model with a population microsimulation. The synthetic population was reconstructed by using local census data [14]. In these studies, however, the police patrolling data (such as the patrol regions, the patrolling frequencies, the shifting schedule, and patrol units) were lacking. Therefore, in this paper, we propose an agent-based model based on both related theories and the expert knowledge, incorporate the GIS and the transportation information of the real city, and apply different types of public data including the police patrolling data to predict the risks of violent crimes.

III. Model Construction

The agent-based model comprises three central parts, the agents identified as the autonomous entities, the environment where the agents move and interact with each other, and the behavior rules that connect everything by specifying how, when, and where the interactions are carried out. The separation of each part gives the model great adaptability to migrate to other locations, incorporate new agents for different environments, and change the agents' behaviors in specific situations. In the model of crime risks, we need to consider the environment, high-risk individuals, police officers, common citizens as the central parts based on empirical research using sociological and psychological theories.

A. Environment

There are three main components in our geographical environment. The first component is the GIS region serving as the boundary for the agents' movements as shown in Figure 1. Because the agents can be placed and travel to any location on the map, the main region limits their movements inside the modeling areas. The second component is a collection of environmental layers with different functional purposes in the model, and each layer comprises various small GIS regions. As shown in Figure 2, a layer of GIS regions for census block groups is constructed so that neighborhood features can be extracted and considered as risk influences when the agents are on the top of any specific small region. The third component is the transportation system to generate the real routing. As shown in Figure 3, given two locations, the agents can move along real paths based on either the shortest distance or the fastest route (display in red dashed line).

GIS regions are created from geographic shapefiles. After extracting the latitudes and longitudes of the regions embedded in the shapefiles, the corresponding GIS regions can be dynamically created. Moreover, by preloading the road

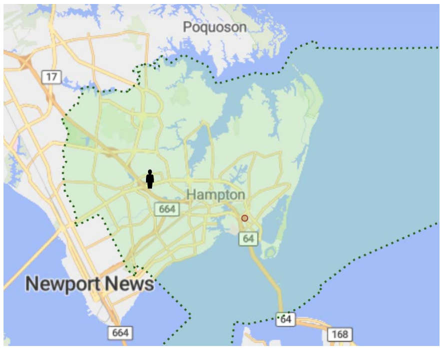

Fig. 1. A GIS region converted from the shapefile.

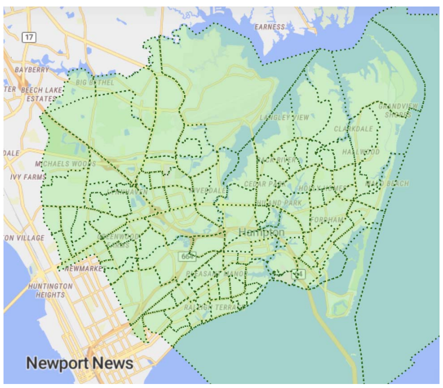

Fig. 2. A layer of GIS regions composed of census block groups.

networks data into the model's transportation system, the previous time lag brought by the massive amount of routing queries with the online server can be avoided.

B. Agents

For violent crime risk predictions, there are three major types of agents in our model: police, common citizens, and high-risk individuals. Each agent follows a rational model of behaviors that can be explained by sociological and psychological theories. Although each type of agents behaves differently, a behavior flow is generalized to fit all agents based on three fundamental elements that cover all the movements both temporally and spatially during the model run: the destination, the time of departure, and the period of stay. As shown in Figure 4, there are only two states in yellow for each agent. The agents either stay at home or stay at some other places. The choice of destinations for other places is considered based on the predefined type of the current agent, the agent's personal preferences, the time of the day, the day of the week, the current location, the weather, and other miscellaneous factors relevant to the theoretical model. The time of the departure is set as a timer that triggers the transition between the two states. For common people during a workday, the timer is set to the next morning when they arrive at home on the previous night. The period of stay is approximated based on the current location upon arrival. If the current location is the workplace, a timer representing the period of stay is set to the evening to trigger the agents' decisions of going back home. Stochasticity is involved in every decision-making process.

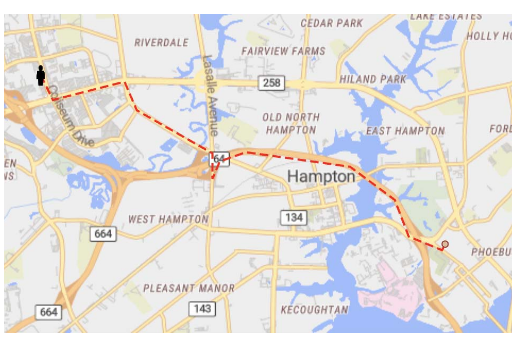

Fig. 3. A real route between two locations.

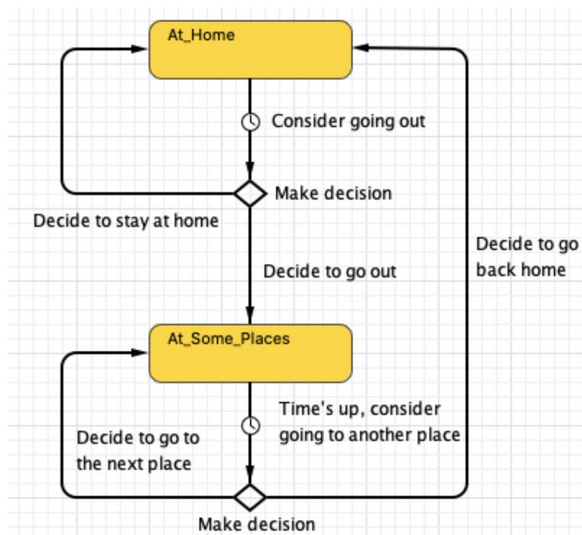

Fig. 4. Behavior flow chart for all agents.

This structure helps the model reduce coupling and maximize cohesion to adapt to new environments or other types of crimes because additional states are rarely needed, and all variations of behavior changes can be fit into the transitions between those two states. Moreover, the interactions between different agents are intangible presences in the model, where the number of different types of agents or crime attractions in the surrounding areas at a specific time and place is either calculated for the risk evaluation or viewed as unpredictable forces that can change the agents' potential destinations or timers. Hence, no structural modifications for this flow are required.

1) Police: The police have always been one of the irreplaceable pieces in crime predictions since they serve as the direct deterrence with a lasting psychological influence over criminals [15]. The various combinations and designs of patrolling strategies on crime reduction have been studied [1], [11]. To fully and accurately capture the predominant effects cast by the presences of the police, we need to understand how the police behave, what their behavior patterns look like, and how they affect high-risk individuals. The ultimate goal is to get a general picture with as many details as possible of how the police are patrolling in the modeling areas and incorporate those details into the model. This information includes the number of the patrolling units, the separations of the patrolling regions, the resting time, the patrolling frequencies, and the moving speed.

2) Common Citizens: Common citizens are one of the major influences of the crime propensity of high-risk individuals, the convergence of different types of people as attractive victims, hot-spots of crimes, and high-risk individuals suggests higher probabilities of street crimes. In previous work, common citizens were often defined universally with the same behavior rules regardless of personal features [1], [11]. In this work, we divide the common citizens into employed people, unemployed people, and children. The above behavior flow gives us the flexibility of defining different types of common citizens to make the overall simulated population representative of the real population in the modeling areas.

Initially, the general public is generated by combining environmental layers with the census data. The agents' home locations are assigned randomly within each small GIS region in proportion to the demographic distribution, therefore, the smaller the scale of the census unit, the more accurate the spatial distribution is. Other relevant features need to be extracted from the census data to categorize people into different groups or identify high-risk victims for the risk evaluation, including but not limited to employment status, age, gender, and education level.

In our model, for each type of common citizens, a corresponding behavior pattern with three components are specified. The first component is the chance when the agents consider going out at different hours on different days in a week. For example, employed people go to work on workdays around 8:00 in the morning while unemployed people may still be at home. The second one is a pool of frequented places. A suitable location needs to be selected based on the current time and location, and a nearby bar may be highly likely at night on Saturday. The third component is a table of an associated period of staying for each location in the address list. For instance, certain types of people such as rebels and innovators [16] tend to stay longer around convenience stores especially during nighttime.

3) High-Risk Individuals and Their Risk Evaluation: High-risk individuals are people with a high propensity to persistently commit violent crimes on the streets selected by the police department using a series of criteria of risk factors, such as history of gang affiliation, violent criminal history. Generally speaking, they usually are gang members who actively roam around crime attractors where people congregate and crime generators where the drug dealing is highly likely to happen, such as malls, convenience stores, and their nearby places. The initialization process of high-risk individuals under the behavior flow is similar to that of unemployed people but with higher chances of going out at any given time, lower chances of returning home before midnight, and a longer list of frequented places for selection.

For each high-risk individual outside their homes, a risk prediction is performed every minute in the model time based on various. Nonetheless, several special conditions force the risk to be 0 without further evaluations of other factors, indicating no risk at all. These conditions include if the agents are within a short distance away from home, if the agents are near police headquarters, or if there are police in the vicinity. The factors examined by the risk prediction process are determined by integrating a series of criminological theories (such as rational choice [6], routine activities [5]) and the practical knowledge of local police investigators and crime analysts. In our model, 38 factors in 7 categories are selected for high-risk individuals' risk predictions.

C. Risk Prediction

For 7 categories of factors in the risk prediction of high-risk individuals: Category 1 is police-related, including the number of police seen in the past day, the number of police seen in the last 10 minutes, the number of police nearby, the distance to the police headquarters, the number of occasions when direct interaction with the police happened in the past day, the number of accompanying associates when direct interactions happen. Category 2 is neighborhood-related, including the population, the count of all past crimes, the count of past violent crimes, the count of past violent crime hot-spots, the number of people who do not have a college degree, the number of people in poverty, the number of people unemployed, and the number of people receiving food stamps, in the current census block group where high-risk individuals are. Category 3 focuses on nearby people within 0.1 miles, including the number of all types of people nearby, the number of high-risk victims (strangers encountered more than three times), the number of females, the number of unemployed people, the number of children, the number of other high-risk individuals, the number of associates, and the number of family members. Category 4 focuses on nearby places within 0.1 miles, including the number of past crimes, the number of past violent crimes, the number of past violent crime hot-spots, the number of past personal crimes, and the number of associates' residences. Category 5 is environment-related, including the distance to home, the time of the day, and the weather condition. Category 6 collects accumulated features, including the distance travelled, the time spent outside, the time spent around violent crime hot-spots, and the number of high-risk victims encountered, all in the past 24 hours. Category 7 focuses on the inherent characteristics of high-risk individuals, including estimated aggressiveness, gang member status, and drug abuser status.

Factors have different weights contributing to their respective category's risk value. Each category also has a different weight contributing to the final risk value. The initial weights for each factor and category are set based on the practitioners' working knowledge and experiences and can be adjusted in the model. The current risk value R_{cur} at any given minute is calculated in Equation (1), where N_C is the number of categories, W_{C_i} is the weight for category i, N_{F_i} is the number of factors in category i, $W_{C_iF_j}$ is the weight for factor j in category i, and F_{C_ij} is the value of factor j in category i.

$$R_{cur} = \sum_{i=1}^{N_C} (W_{C_i} * (\sum_{j=1}^{N_{F_i}} W_{C_iF_j} * F_{C_ij})) \tag{1}$$

Since the past has a lasting influence over the present, the final risk value R_f for the current minute is calculated in Equation (2), where W_{past} is the weight of past risks set as 0.2, R_{avg} is the average risk value of the past 1,440 minutes, and $W_{present}$ is the weight of current risk set as 0.8.

$$R_f = W_{past} * R_{avg} + W_{present} * R_{cur} \tag{2}$$

IV. A Case Study

In this work, we use Hampton, VA, USA as an example to predict high-risk individuals' likelihood of committing street violent crimes within the jurisdiction. Hampton has an estimated population of around 130,000 over 136 square miles, where people rely primarily on personal vehicles for commuting instead of public transportation. Below we provide the detailed information about related data and parameter settings.

A. Data and Source

One of the model's defining advantages is its adaptability towards different environments and modeling areas by incorporating comprehensive and publicly available data into the model. All required types of data with their sources are listed in Table 1. Based on the description of each data's usage, latitudes and longitudes of GIS regions are extracted from all kinds of shapefiles to form functional environment layers, and therefore, specific locations can be generated randomly inside or outside a region. Various features of the current neighborhood where the agents' are located can be accessed by checking the underlying GIS region. There are 34 census tracts for population distributions as shown in Figure 5, and distinct density differences can be observed in different census tracts. There are 98 census block groups in the city as shown in Figure 2.

Each important feature selected for common citizens is assigned following the distribution of the demographic data. The transportation data that include road networks can avoid constant route queries with the online map server during the simulation. Real weather data with days of inclement weather recorded is critical in predicting past crimes. Patrol regions for different police units are often private and can only be attained by working with the local police agency.

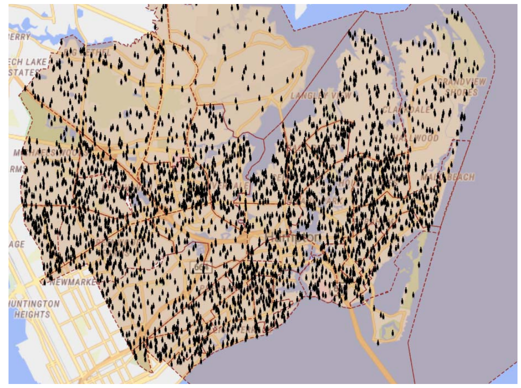

Fig. 5. The distribution of population in all census tracts of Hampton.

In general, two years of crime data suffice to reflect each neighborhood's current crime rate and generate an accurate distribution of violent crime hot-spots. There are seven months' total of 4,479 crime records from May 2019 to October 2019 in our model, where 495 are violent crimes. As one of the key components in the risk evaluation, the top 100 violent crime hot-spots are shown in Figure 6, and the number of violent crimes for each hot-spot reported within 0.06 miles is calculated and shown on top of the location.

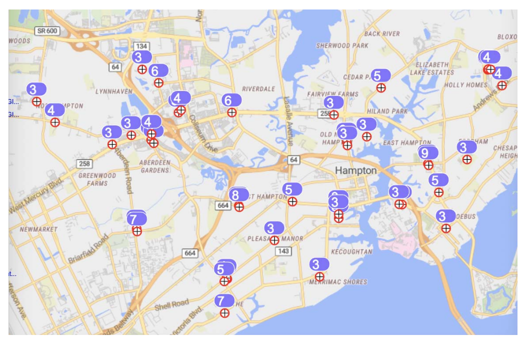

Fig. 6. The top 100 violent crime hot-spots in Hampton.

B. Model Parameters

All the model's key parameters are listed in Table 2. It is noted that the parameters are not fixed and can be adjusted for different applications. In this work, we set the parameters according to the public data and the expert knowledge, such as the patrolling schedule, the population distribution, and the available computing resources.

V. EXPERIMENTS AND RESULTS

We implement the model using AnyLogic [17], one of the most widely used agent-based simulation tools. We use seven months' crime records in Hampton in the model, and the simulation period is set for one month. The simulation is carried out on a personal Macintosh computer with a memory

TABLE I
SUMMARY OF DATA REQUIRED FOR THE SIMULATION WITH THEIR USAGES AND SOURCES

Data	Usage	Source
City boundary shapefile	Used for limiting the agents' movements inside the city	www.census.gov
Census tract shapefile	Regions used for assigning the number of agents based on the demographic distribution of the population	catalog.data.gov
Census block group shapefile	Regions (smaller than census tract) used for evaluating neighborhoods' features, such as crime rate and unemployment rate	catalog.data.gov
Water areas shapefile	Unreachable regions in the city	catalog.data.gov
Forest areas shapefile	Unreachable regions in the city	www.geofabrik.de
Land-use shapefile	Extracted recreational and industrial areas are used for assigning workplaces to common citizens	www.geofabrik.de
Demographic data	Used for initializing features of common citizens based on population distribution	data.census.gov
Transportation data	Offline routing	www.geofabrik.de
Weather data	A critical influence on the agents' decision-making process of going out and the risk evaluation	www.ncdc.noaa.gov
Police patrol region shapefile	Used for generating patrol points for the police	Hampton Police Department
Crime data	Used for generating violent crime hot-spots and the risk evaluation	cityprotect.com
Local airbase shapefile	Unreachable regions (guarded military base) in the city	catalog.data.gov

TABLE II
MODEL PARAMETERS

Variable	Description and Rationale
Number of patrolling units=16	Information from the police agency
Number of high-risk individuals=100	Estimated by the police agency
Number of common citizens=3,000	A population capable of reflecting the general travel patterns of all citizens in the city
Travelling speed =20 miles/hour	All agents currently travel at the same speed
Perception distance=0.1miles	Based on the relative length of one block in Hampton, the perception distance is the radius of the agents' ability to perceive other agents and locations' presence
Probability of going out when the weather is inclement=0.3	When the weather is inclement, the probability of making the decision of going out during the stochastic decision- making process for high-risk individuals
Patrolling frequency: all day patrolling with 5 minutes day time rest and 20 minutes night time rest	Each police unit patrols 24 hours a day in their assigned patrol regions. When the destination is reached, it rests for 5 minutes between 10 p.m. to 7 a.m. and 20 minutes between 7 a.m. to 10 p.m. before moving to the next randomly generated patrol point
High-risk individuals with replacement=false	To maintain the relations between high-risk individuals, during the simulation, once a high-risk individual commits a crime, instead of leaving the model, the agent then goes back home and rests for 48 hours before going out again

of 32 GB. Figure 7 shows all 495 violent crimes of Hampton in the past seven months using the heat map. In the figure, the concentration of the crimes is reflected by the colors and the sizes of the points. The bigger the dots, the more crimes there are nearby. From the figure we notice that the violent crimes occur around the entire city and each region has several spots with more crimes, which should draw more attention.

A high risk value suggests a probable crime incident. When the risk value exceeds a predefined threshold, a high-risk incident occurs. We run the simulation for one month, the predicted high-risk incidents are shown in Figure 8. In the figure, we use the colors and the sizes of the points to represent the density of these high-risk incidents too. Bigger dots indicate more nearby incidents. The number of predicted incidents is 82, which is close to the average number of violent crimes each month in the past seven months. From the figure, we see that there are three clusters of incidents in the predicted month. The majority of the predicted incidents are in the northwestern part of the city along each side of the interstate highway 64, which is also evident in the past crime distribution as shown in Figure 7. The place with the most incidents is Coliseum Central, one of the busiest commercial areas in Hampton. Its dense population and traffic flows are possible reasons for the high incident rate. Additionally, 82% of the predicted incidents are within 0.1 to 0.5 miles of a real violent crime hot-spot. Six blocks cover 93% of the predicted incidents, which are among the top 9 blocks that cover the most real violent crimes in Figure 7.

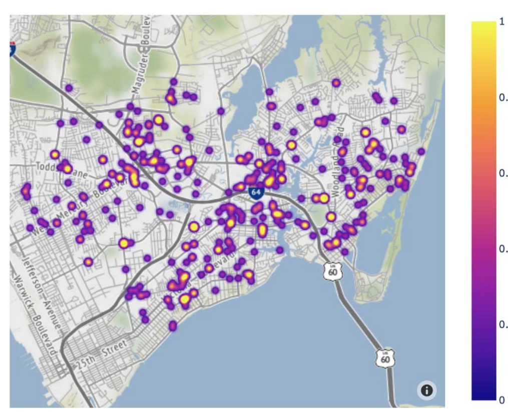

Fig. 7. Heat map of all violent crimes of Hampton in the past 7 months.

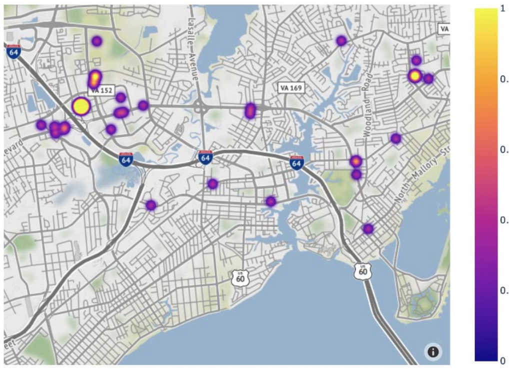

Fig. 8. Heat map of predicted violent high-risk incidents of Hampton in the predicted month.

VI. Conclusions and Future Work

This paper presents a complex and easily reproducible predictive model for the risks of street violent crimes for high-risk individuals based on the theoretical and empirical knowledge. This model adopts the agent-based modeling method and incorporates the publicly available data, including the crime data, the census data, and the environment data. The proposed behavior flow is highly adjustable for agents with dramatically different life patterns in different environments and target selections in other types of crimes, such as burglary. The case study conducted on Hampton demonstrates the model's ability to predict the risks of street violent crimes. We will extend our work in the following directions. First, we will further tune the parameters and conduct sensitivity analysis for its easy adoption of other applications. Second, we will validate our model by collecting more real violent crime data to show its effectiveness. Third, we will apply this model during the implementation of a person-based deference policy to improve the policing practices.

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