Urban Crime Mitigation
A Model to Derive Criminal Patterns and Determine Defender Placement to Reduce Opportunistic Crime

Solomon Y. Sonya, Luke Brantley and Meagan Whitaker
Departments of Computer Science and Operations Research, U.S.A. Air Force Academy, 2534 Fairchild Drive, U.S.A.F Academy, Colorado, 80840, U.S.A.

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Abstract: Urban opportunistic crime is a problem throughout the world causing financial, physical, and emotional damages to innocent citizens and organizations. Opportunistic crimes require minimal reconnaissance and preparation in order to conduct an attack (e.g., burglary, robbery, vandalism, and assault). Opportunistic criminals are more spontaneous in nature making their actions difficult to anticipate and create an approach to reduce these crimes. Statistical analysis of crimes may reveal distinct patterns from which a strategy can be created to better mitigate future crimes. This paper describes analysis performed on real-world campus crime data in which distinct correlations were discovered to determine the significant factors that motivate opportunistic crime. This research concludes by developing a dynamic defender placement strategy that adapts over time to reduce the utility of opportunistic crimes. The research contribution allows for the determination of significant factors motivating opportunistic crime and releases a program that maps crime occurrences over time, determines the minimum defender allocation for a given area, and dynamically specifies defender placement strategy to mitigate future crime. The novelty of this approach allows for application to other campuses, shopping complexes, and living districts to form conclusions about opportunistic criminal activity and formulate an approach to abate such crimes.

1 INTRODUCTION

Opportunistic crime is a serious problem affecting urban areas. As opposed to well-planned and coordinated attacks (e.g. terrorist attacks or gang influenced violence), opportunistic crimes are rather spontaneous in nature and involve very little premeditation enabling the criminal to execute an attack based on the opportunities present at a given time. For instance, you may have heard of stories where a person momentarily leaves their phone, wallet, or purse unattended, walks away to accomplish a task only to return and discover that their personal items have been stolen within minutes of stepping away from the area. This would be an example of an opportunistic crime in which a criminal carries out an attack based on maximizing their utility over the defender's protection strategy.

A defender is a police officer or crime abatement personnel whose presence and action is used to reduce crime. The utility for an opportunistic crime is defined as the motivation and expected outcome of a criminal succeeding with the attack without being apprehended in response to the defender's strategy (Chao et al, 2015), (Yildiz, 2002), (Osborne and Rubinstein, 1994). Other types of opportunistic crimes include burglary, robbery, grand theft auto, trespassing, assault, and vandalism. In all, these crimes are quite costly and produce damaging effects on the population.

Attractiveness is used to measure the influences of opportunistic crime around a specified area. A region that exhibits more opportunistic crime than another region is said to be more attractive to opportunistic criminals. However, it is necessary to bind several research questions around this concept in order to better scope how to determine the attractiveness of area. For instance, how is a criminal's utility impacted by the attractiveness of an area and does this attractiveness remain static or change over time? How can external influences (e.g., holidays, special events, football, basketball, soccer games, and campus parties) influence the attractiveness of an area? Finally, if we can

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determine the significant factors that affect attractiveness of opportunistic crime, is it possible to deploy a better defender allocation strategy to mitigate these crimes and if so, how and when should we update this strategy? The goals of this research are to study this concept in further detail.

Currently, University XYZ manually assigns the defender placement and patrol strategy to cover the campus in hopes of deterring crime. This approach has proven to be quite time consuming and ineffective at mitigating crime (Chao, Sinha, Tambe 2015). NOTE: the true name of the university is masked to protect the identity of the school. In this research, we devised an approach to analyze the university crime data to create an appropriate model that learns the significant factors affecting opportunistic crime over time. This allows us the ability to describe the underlying data and formulate a dynamic assignment strategy to better reduce crime.

The end result of this analysis reveals the motivating factors that contributed to the attractiveness for a criminal to commit an opportunistic crime. Based on these factors, we are able to calculate the placement of a visible defender to deter future crime. This same approach can be adapted to additional areas exhibiting opportunistic crime such that motivating factors can be discovered and a better patrol strategy devised to reduce crime.

2 BACKGROUND AND RELATED WORK

The idea to examine opportunistic crime originated from the Department of Homeland Security funded CREATE (Center for Risk and Economic Analysis of Terrorism Events) group, based at the University of Southern California (USC). A new framework to create a patrol allocation schedule around adaptive opportunistic criminals was introduced in "Keeping pace with criminals: Designing patrol allocation against adaptive opportunistic criminal" by Chao Zhang et al. In this research, Chao Zhang et al applied game theoretic approaches on real-world campus crime data to map the interaction between patrol officers in moving vehicles and criminal activity. This behavior was mapped as parameters in the Dynamic Bayesian Network (DBN) in order to learn the appropriate model and account for hidden states which included the true number of criminals and patrol officers present in the area and the impact their presence may have on each other.

In addition to mobile police patrols around the campus, University XYZ also employs visible, well-identified campus security guards who remain relatively stationary to an assigned grid location. This research applies pattern recognition and statistical analysis for the assignment of these visible, pedestrious defenders whose presence at the appropriate location is used to deter crime via classical conditioning.

Classical conditioning is a model of learning that deals with the automatic, instinctual response of a person in response to apparent stimuli (Hall, 1998). Classical conditioning is applied to this research to hypothesize appropriate response of a criminal's actions as a result of a visible defender present within an area.

The Cheater Model further helps to refine the hypothesized relationship between defenders and crimes. According to this economic theory, many people may allow themselves to cheat or conduct some form of unscrupulous activity when the marginal utility to do so is greater than the marginal costs and consequence of the activity (Nagin, 2002). An experiment was held with varying levels of monitoring over employees known to inflate the truth about their self-reported performance. The study showed that as perceived monitoring decreased, cheating increased.

Additional research determined that criminals react inversely to the number of defenders present at a location. In "Crime and Human Nature: The Definitive Study of the Causes of Crime," researchers Wilson and Herrnstein confirmed that the defender/criminal relationship is determined by classical conditioning. We use this knowledge along with the Rational Cheater Model to assert that an increase in defender presence should decrease crime in an area. The locations of these defenders however, will be crucial in having an impact to the expected crime level. The following sections state how analysis of crime data can indicate the location at which to place a visible defender to mitigate opportunistic crime.

3 RESEARCH HYPOTHESIS

Attractiveness of opportunistic crime may be dependent on time, population, and the number of defenders present during an incident. The proportionality of crime discovered should reflect the proportionality of defenders assigned to an area Studying this interaction helps to predict the likelihood of future crimes and efficiently assign defenders to the appropriate areas of highest attractiveness.

The following research questions help direct the study of our hypothesis:

1. What effects (if any) do the following factors have on the attractiveness of opportunistic crime:
   - **Time of Day**: i.e., how does the time of day affect the prevalence of crime?
   - **Day of Week**: i.e., which days are more likely to experience a proportionally higher number of crime?
   - **Week of Year**: i.e., is it possible to determine which weeks of the year experience a higher percentage of crime?
   - **Special Events**: i.e., is it possible to determine how special events (e.g. football/basketball games, holidays, and campus parties) influence crime?
   - **Physical Location**: i.e., is crime uniformly distributed across the campus area or which areas have a greater propensity for opportunistic crime?
2. In an area that exhibits attractiveness for opportunistic crime, what is the minimum number of defenders required to cover an area, and where should we assign these defenders?
3. Given a defender assignment strategy, when should we update the patrol allocation in order to maintain the best utility for defenders to deter crime?

4 METHODOLOGY

The methodology in this research is divided in two sections: Data Analysis and Patrol Schedule Assignment. The Data Analysis section determines the significant factors affecting opportunistic crime and displays crime patterns learned from the data set. The Patrol Schedule Assignment section creates the estimator of when and where crime may occur and applies significant aspects of crime learned over time to produce the dynamic assignment of defenders to the areas exhibiting the highest likelihood for a repeatable crime.

5 EXPERIMENT SETUP

University XYZ supplied an archive containing three years of crime data between 2011-2013 and a map of the university dividing the campus area into five police patrol zones. Figure 1 depicts a very short description of crime data received by the university. Certain attributes regarding the analyzed data are masked to protect the identities and locations and individuals involved in the incidents.

Zone	CaseNbr	address	Classification	Date	Time	ListValue
A	Masked	Masked	BATTERY	11/30/2013	18:10	Classroom/Research
A	Masked	Masked	DISORDERLY CO	11/30/2013	14:45	Classroom/Research
B	Masked	Masked	BATTERY	11/30/2013	20:40	Street Intersection
B	Masked	Masked	PROPERTY	11/30/2013	21:25	Restaurant
A	Masked	Masked	BATTERY	11/30/2013	20:30	Street Intersection
B	Masked	Masked	ALCOHOL	11/30/2013	19:49	Restaurant
A	Masked	Masked	BURGLARY	11/30/2013	16:35	Administration Building
A	Masked	Masked	DISTURBANCE	11/30/2013	18:24	Athletic Field
A	Masked	Masked	FORCIBLE SEX O	11/30/2013	22:25	Classroom/Research
C	Masked	Masked	NARCOTICS	11/30/2013	20:20	Sorority
C	Masked	Masked	PROPERTY	11/30/2013	16:00	Fraternity

Figure 1: Crime Data Subset.

The data set from the university included crimes classified into 50 different categories of crimes. We combined these classifications and reduced our analysis to focus primarily on crimes relating to Theft, Destruction of Property, and Assault categories as these are the main types of opportunistic crimes studied in this research. Figure 2 depicts a breakdown of this chart. Figure 3 depicts the campus response area protected by the police patrols. Zone A encompasses the majority of university classrooms and laboratories. Zone B encompasses the recreational areas including the football and sports arenas. Zone D is the primary location of on-campus housing. Zones C and E are additional residential areas further away from main campus.

Theft	Destruction of Property	Assault
Burglary	Arson	Assault
Burglary-Motor Vehicle	Trespass	Assault-Other
Burglary-Other	Vandalism	Battery
Fraud		Criminal Threats
Identity Theft		Domestic Violence
Property		Forcible Sex Offense
Robbery		Harassment
Theft-Access		Kidnapping
Theft-Fraud		Homicide
Theft-Grand		
Theft-Grand Auto		
Theft-Grand Person		
Theft-Motor Vehicle		
Theft-Petty		
Theft-Trick		

Figure 2: Crime Description.

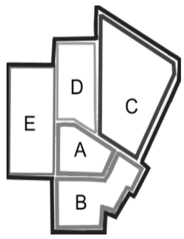

Figure 3: Area Map.

6 EXPERIMENTATION AND DATA ANALYSIS

We divide the research questions identified in Chapter 3 into several experiments to form appropriate conclusions regarding the underlying data set.

6.1 Time of Day Experimentation

This experiment determines if the hour of the day is significant when categorizing types of crime. We hypothesize since human activity varies throughout the day, crime may follow a similar trend. We performed a frequency analysis across the data set and graphed the results in Figure 4. This revealed how time of the day influenced the prevalence of crime.

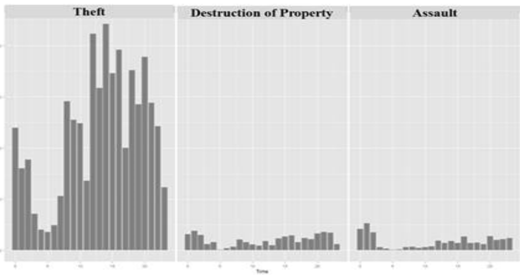

Figure 4: Crime Frequency Distribution by Hour.

Theft accounts for the highest occurrence of crime within this data set mostly occurring between 1300 and 2000. The majority of destruction crimes occur between 1900 and 0100. Finally, the majority of assaults occur between 1900 and 0200. Overall, we conclude the hour of the day has an effect on crime and will remain a significant factor in our analysis for determining the optimal defender assignment strategy.

6.2 Time of Day Experimentation

This experiment determines how the day of the week affects crime in various zones. We hypothesize that if human activity varies based on the day of the week (especially on weekends) then crime should follow a similar trend. We isolated crimes reported on each day of the week and further separated these crimes into the respective zones reported for each crime. Figure 5 depicts the frequency distribution of crimes reported within each zone.

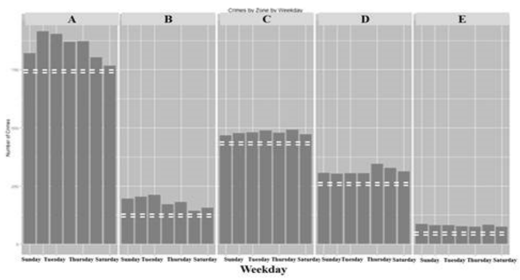

Figure 5: Frequency Distribution by Day of the Week.

In this experiment, we expected to see weekend days display a greater statistical significance of crimes than normal weekdays. However, this was not the case from our data set. Zone A has the highest concentration of crime. This is expected because Zone A covers the majority of the university area and campus buildings. With respect to each zone however, crime remained relatively similar across each day of the week. Since day of the week was not observed to have a significant impact on the number of crimes committed, this factor is excluded from our analysis model.

6.3 Week of the Year Experimentation

Experiment 3 determines how the week of the year may affect crime. Spring, summer, and winter semesters are distinct times in which population varies on a college campus. We hypothesize crime patterns may follow the population throughout the year. Figure 6 depicts the frequency distribution created by separating crime occurrences by week of the year divided into the five main patrol zones.

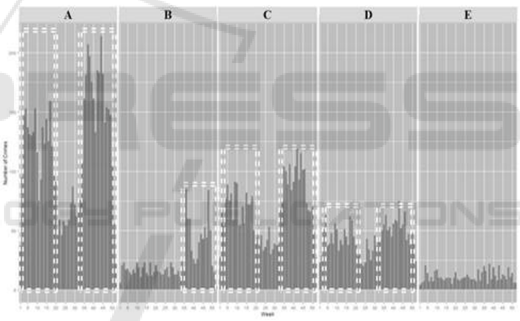

Figure 6: Frequency Distribution of Crimes by Week.

Crime trends within Zones A, C and D display distinct trends pertaining to the spring, summer, and fall semesters for the university. Considerably less crime occurs during the summer weeks than during the semesters for which most of the student body is present for classes. Zone B exhibits a significant spike in crime activity between weeks 36 through 48. Zone B contains the football coliseum. Upon further investigation into the campus activity during these weeks in Zone B, we discovered week 36 is when home football games occur for the university. In addition, many home games occur at the coliseum during the fall semester. It is evident that crime follows this trend as well. From this experiment, we conclude the week of the year is a significant factor affecting opportunistic crime.

6.4 Special Events Experimentation

In this experiment, we wish to determine the relationship between crimes around dates of special events to identify the specific events that account for a higher percentage of campus crime. We hypothesize if crime seems to follow population, then crime should increase during special events, however, it is unknown if the increase in crime is uniform for every event or which special events account for a higher rise in crime. We first analyze the overall times when crimes occurred to give us an idea of the average crime distribution by hour. This is noted as “All Crime” in Figure 7. Next, we combine the schedule of special events for baseball, basketball, and football games, fall move-in period, and homecoming week to produce the frequency distribution depicted in Figure 7.

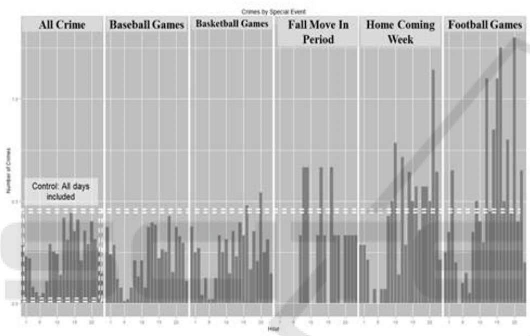

Figure 7: Crime Distribution Around Special Events.

When comparing the average number of crimes on a normal day, we determined baseball games, basketball games and fall move-in period do not have a considerable effect on crime. The average number of crimes for homecoming week and football games are considerably higher than the average number of crimes per hour. We conclude from this experiment that certain special events are a significant factor affecting opportunistic crime.

6.5 Crime Densities via Clustering I

Experiments 5 through 7 determine the locations within zones when and where crimes densities peak. We created a separate address to latitude/longitude derivation process in order to convert the recorded addresses into coordinates for plotting and organization into distinct clusters. The cluster movements are tracked over time in order to observe their patterns and distinctions.

Experiment 5 determines the specific areas with the highest overall densities of crimes. We hypothesize crime is not uniform, but may be concentrated around certain areas within the university patrol area. Discovering the locations with highest densities of crime helps to reduce the search space and allow concentration of defender allocations around areas exhibiting the greatest clusters of crime. Experiment 5 uses the Partitioning Around Medoids (PAM) algorithm to provide a more precise clustering of crime densities. We represented the lines of longitude across the X-Axis and plotted the lines of latitude across the Y-Axis. Figure 8 depicts the result from plotting the clusters of crime.

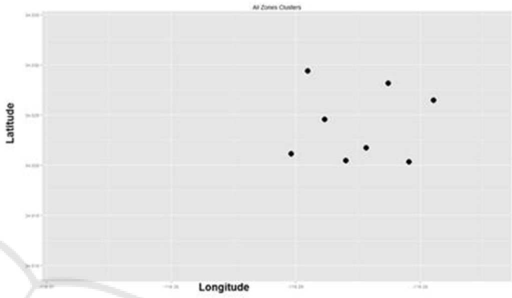

Figure 8: PAM Clustering Crime Densities by Location.

Clustering has proven to help identify areas of highest attractiveness and can reduce the focus area to locations exhibiting highest densities of crime.

6.6 Crime Densities via Clustering II

The purpose of this experiment is to identify specific addresses with the highest overall densities of crime. We hypothesize crime may follow streets, thus, analyzing occurrences by street should identify densities of crime as well. The frequencies of crime by street are measured, a ceiling and floor function is used to calculate the centroid address around most crimes on each street, and then the derived coordinates of the centroid are mapped to produce the crime densities as shown in Figure 9.

Figure 9: Clustering Crime Densities via Street Address.

We conclude mapping crime occurrences to streets may be used to determine the areas of highest attractiveness as well. We used two separate approaches to plot the densities of crime. We used the statistical programming environment, R, to analyze the data and conduct the PAM clustering in Experiment 5. We wrote a program to derive this data and interface with Google Maps to allow the observer the ability to view areas of highest attractiveness along with additional parameters we discovered during this analysis in Experiment 6. The two separate approaches revealed the same clustering which validated our methodology to map criminal activity around clusters of repeated crime.

6.7 Crime Density Movement by Time

This experiment determines specific times and addresses within each zone where crime densities peak. We hypothesize mapping crimes to clusters may determine areas of highest attractiveness such that observing when crime clusters shift may identify how to update the patrol strategy to follow criminal behavior. Figure 10 is an overlay of opportunistic crime observed using R and our program to map the hour and location where crime occurred.

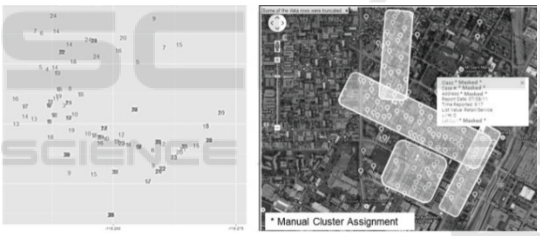

Figure 10: Clustering Crime Densities Over Time.

Analysis of these clusters indicate a procedure to map crime densities by time along street addresses and notifies when to update the defender assignment strategy based on the movement of crime clusters.

6.8 Data Analysis Conclusions

It is possible to determine how certain factors affect attractiveness of opportunistic crime. The frequency distributions and cluster analysis allowed us to make several conclusions on how to learn details regarding the data set. Time of day, week of year, special events, and location are significant factors in determining when and where crime occurs. Mapping densities of crime as a function of time will help to identify locations to place a defender and when to adjust the visible defender assignment strategy.

7 DEFENDER ASSIGNMENT

This chapter incorporates the significant factors identified in Chapter 6 to create the patrol schedule to reduce opportunistic crimes. We require the following information in order to make an efficient defender assignment:

1. Proportionality of crime per street per hour
2. Acceptable crime threshold (defined by user)
3. Coverage area (***CA***) required for each street
4. Defender Presence Radius (***DPR***)
5. Defender Compression Factor (***DCF***)

The proportionality of crime per street for each hour is calculated in Chapter 6. Our program analyzes the number of incidents on every street for each hour and normalizes this ratio across all applicable crimes recorded to calculate this proportionality. The user-defined threshold represents the minimum percentage to view crimes across the entire data series. For instance, data analysis conducted in this research spans a few square miles with years' worth of recorded data. A single crime incident within the entire data series is statistically insignificant when making generalizations regarding trends across the entire population. Multiple crimes across several years within the same area allow for a more accurate generalization regarding likelihood of a future crime within the same area. A larger threshold reveals a larger prevalence of crime. Based on user specified threshold (percentage), streets with applicable crime events meeting the minimum threshold percentage are populated for consideration in the defender assignment function detailed below.

Coverage Area (CA) specifies the total length (defined by crime occurrence clusters) required for protection by defender(s). We used the haversign formula to calculate the great-circle distance between crime clusters on each street. This identified how much space is required for protection by a defender.

Defender Presence Radius (DPR) is the effective distance established by a visible defender to discourage crime (via classical conditioning). The **Defender Compression Factor (DCF)** represents the multiplicative effect additional defenders assigned in the same coverage area have on the DPR. For example, let the coverage area for a particular street be 8000ft. Further, let the DPR be 800ft. A naïve defender assignment can be specified as minimum_defender_count = CA / DPR. Thus, we can ascertain 10 defenders are required to cover this area. However, applying classical conditioning to rational criminal behavior patterns, we postulate the more defenders placed on a street should increase the individual DPR such that a criminal successively observing only a few defenders (say 5 or 6 defenders along the same path) could conclude additional defenders are likely nearby. The criminal would opt to move away from this location. This results in successfully reducing the criminal's utility to attack by using a reduced number of defenders.

Opportunistic criminals subconsciously observe the DCF and DPR to calculate their utility in succeeding with the attack. Future research will be required to know how the coverage area expands as a function of the number of defenders present. In this research, we assigned the DCF to 1.8 and DPR to 800ft. Taking the DCF into account, we can calculate the minimum number of defenders (*d*) required with respect to coverage area for each street (*s*) meeting the user's threshold to be:

$$\boldsymbol{min_s(d) = DCA_s / (DPR * DCF)}$$

The aggregation of the minimum defender count per street given a specified threshold parameter produces the minimum number of defenders required to protect an area and more importantly, specifies the location at which the defenders are assigned. Figure 11 depicts a final output from our program displaying the assignment of each defender for each particular hour.

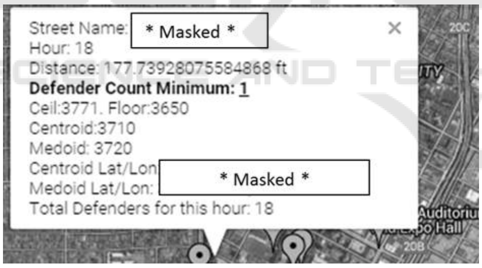

Figure 11: Minimum Defender Allocation.

8 CONCLUSIONS

Opportunistic crimes require minimal reconnaissance and preparation in order to conduct an attack. The damages of such attacks can be extremely costly to the population. This research presented a new approach to apply frequency analysis coupled with density distributions to determine the significant factors that affect the attractiveness of opportunistic crime and produce a methodology to mitigate these crimes. Based on the data set analyzed in this research, time of day, week of year, special events, and location are significant factors in determining when and where crime occurs. Placement of a visible defender can be determined by the significant factors uncovered in this research, proportionality of crime, crime coverage area, defender presence radius, and the defender compression factor. This research introduced the methodology of using these factors to allow for the generation of a defender placement strategy aimed at maximizing a visible defender's utility to reduce opportunistic crime. The novelty of this approach allows for application to other large campuses and living districts to form conclusions about opportunistic criminal behavior patterns and formulate an approach to abate such crimes.

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