Optimal Temporal-Spatial Deployment of Urban Law Enforcement Personnel: Theory, Analysis and Implementation

By

Seung Hyeon Nam

Submitted in partial fulfillment of the requirements for the degree of Bachelor of Science in Engineering Department of Operations Research and Financial Engineering Princeton University

Advised by Professor Alain Kornhauser

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Honor Pledge

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Seung Hyeon Nam
I would first like to thank my advisor, Professor Alain Kornhauser, for not only suggesting my thesis topic, but also for continually offering sound advice despite the numerous difficulties encountered during the formulation of this thesis. I consider myself very fortunate to have had an advisor who allowed freedom both on the conceptual process as well as on the topic itself. I would also like to thank the Computer Science department for providing assistance during the programming process of this thesis.

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Again, to all my friends and family: a thousand times, Thank You.
Abstract

Inspired by a previous experiment conducted by UCLA’s UC MaSC project for the Los Angeles Police Department, this paper combines and builds upon the underlying principles of using analytical and computational models of crime pattern formation to simulate criminal activity with a focus on residential burglary. Previous models have assumed fixed concepts that are expanded upon and theorized in this paper, including questions regarding police-criminal interactions, burglar mobility, non-dynamic base site attractiveness, alternate policing patterns, geographical limitations, and others. The analysis and resulting conclusions are aimed at improving current methods of crime prevention, as well as the creation of a location-independent computer program, adaptable to any urban environment.
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1. Introduction

Given the natural lack of ideal resources, police departments must suffice with limited policemen and vehicles to patrol and best combat crime throughout their precincts. One example of a classic qualitative method employed by enforcement agents throughout the world is to spread patrolmen throughout an area with concentration on specific areas suspected of being particularly important, and responding to calls efficiently given an effective spread over an area utilizing basic patrolling routes. This is one time-proven method of crime management; however, increasing challenges to respond quicker to an ever-growing population has proven the need for a more precise science of crime prevention applicable independent of location, rather than on qualitative judgments based on past expectations.

The objective is therefore to establish a system in which data, both past and present, can be extrapolated upon to assist police departments simulate criminal activity, thereby allowing the implementation of police countermeasures that will result in the maximum prevention of criminal activity, or at the very least, improving with the fastest response times with the necessary tools for the specific crime committed. The required simulations and crime prevention methods can be based on basic principles that can be feasibly modeled with modern and relatively manageable computer programming techniques.

However, there are significant difficulties in achieving such a system. Though crime locations and types can be modeled using stochastic systems and thus used to
predict locations of certain crimes, the real world of crime has many more influencing factors that may render the simple models useless. Complicating factors may include, for example, reactions to a change in police patrolling routes, which therefore could negate any positive benefit from changing the current system. Another such complicating factor may be gang rivalries and dynamics; for example, eliminating a gang or cracking down on its influence may have effects on other gangs, and such crime patterns may change based on the actions of the police. There are a multitude of other factors, and in order to compile a working model that will be effective enough for actual use, the most important concepts must be chosen and integrated together.

The primary reason for this paper’s focus on residential burglary is practicality. Residential burglary is the simpler of crimes due to the stationary nature of the target, and the relatively understandable nature of the burglar. Moreover, by focusing on residential burglaries, we can create a model applicable to a wide variety of residential areas, rather than ones complicated by a multitude of difficult-to-model external factors including gang violence and urban culture.

0.1 – Background (UC MaSC Case Study)

The UC MaSC project was a large-scale and long-term project headed by four professors (J. Brantingham [UCLA Anthropology], A. Bertozzi [UCLA Mathematics], G. Tita [UCI Criminology, Law and Society], L. Chayes [UCLA Mathematics]) and assisted by five post-docs, six PhD candidates, with multiple undergraduate and former students. The
project officially dates back from 2008 – onwards, though research and publications have been referenced from similar work accomplished in the early 2000’s.

Following nationwide media coverage in late 2011 from national media firms including the New York Times, the UC MaSC (“Mathematical and Simulation Modeling of Crime”) project has gained credible traction as a viable application of mathematical and statistical modeling for predictive policing. The overarching objective is to apply mathematical and statistical modeling and theory to historical criminal data, with the goal of better predicting and therefore better combating crime.
At the core of the UC MaSC system lie the statistical models that allow for the mapping of historical data into usable theoretical distributions. As this thesis is based around similar modeling techniques, the UC MaSC papers are naturally instrumental for this thesis. Additional literature useful for developing the expanded model is also included.

2.1 – M. B. Short et al. (2008)

A Statistic Model of Criminal Behavior

This paper primarily focuses on formulating a quantitative mathematical model (both discrete and continuous) that aims to replicate the effects of hotspot formation for criminal behavior; the primary example used is residential burglary. The overall result is the observation that given certain assumptions, hotspot formation is related to the number of days simulated, as well as the rate of criminals appearing.

The key assumptions are as follows:

- Attractiveness of a residential house to a burglar is represented as a linear equation with a static variable as well as a dynamic one which represents the component associated with “repeat and near-repeat victimization.”
- The dynamic component of attractiveness is assumed to be influenced by the previous time interval’s dynamic component, a time-related decay, as well as the
number of burglaries in the previous time interval. An optional (and implemented in this thesis) assumption is to include the “broken windows” effect, which reflects the often-observed real-world result that neighborhood conditions have an effect on the target site’s burglary rate.

- Burglary is a random event, represented by a standard Poisson process that takes into account Attractiveness as well as the interval of time the burglar spends in that location. If burglary does occur, the burglar will be removed from the system in order to resemble how burglars flee the scene and lay low after robbery. If burglary does not occur, the burglar will move to an adjacent location based on random walk probabilities weighted by attractiveness.

- In order to simulate burglars becoming active again after robbery, a rate of spawning is determined per lattice grid.

This thesis shall only focus upon the discrete portion of this paper, due to the purpose of simulating realistic discrete worlds. The relevant modeling equations utilized from this paper (M. B. Short et al.) are as follows:

- Attractiveness at site $s$ is defined by the sum of a static variable $A^0_s$ and a dynamic variable $B_s(t)$. This paper assumes $A^0_s$ as a constant across the field, which will not be assumed in the final model of the thesis.

\[ A_s(t) \equiv A^0_s + B_s(t), \]
• Burglary at site \( s \) is defined by a Poisson process probability \( p_s(t) \) where the expected number of burglaries per \( dt \) is \( A_s(t)dt \).

\[ p_s(t) = 1 - e^{-A_s(t)\delta t}. \]

• If the burglar does not burglarize at site \( s \), it will move to an adjacent site \( n \) (one of: up, down, left, right in a discrete model) as a random walk with probabilities \( q_{s\rightarrow n}(t) \) weighted by attractiveness from adjacent sites \( s' \):

\[ q_{s\rightarrow n}(t) = \frac{A_n(t)}{\sum_{s'\sim s} A_{s'}(t)}, \]

• Depending on the choice of assumptions, one can choose to ignore the “broken windows” effect, where the neighborhood attractiveness has an effect upon the target site attractiveness. Thus the dynamic portion of attractiveness \( B_s(t) \) would comprise of the attractiveness at the previous interval multiplied by a time decay factor \((1 - \omega dt)\) and added to a factor \( \theta \) multiplied by the number of burglaries at that site in the previous time interval \((E_s(t))\):

\[ B_s(t + \delta t) = B_s(t)(1 - \omega \delta t) + \theta E_s(t), \]

• If including the “broken windows” effect (as will be implemented in this thesis), an average of the neighboring sites using a weight \( \eta \) is included:

\[ B_s(t + \delta t) = \left[ (1 - \eta)B_s(t) + \frac{\eta}{2} \sum_{s'\sim s} B_{s'}(t) \right] (1 - \omega \delta t) + \theta E_s(t), \]
The aforementioned equations will be utilized as the foundation of this thesis’ computer program and simulations.

2.2 – L. M. Smith et al. (2010)

*Improving Density Estimation by Incorporating Spatial Information*

This paper primarily focuses on determining the best density estimation tools from a given set of methodologies for mapping crime, assuming that the location of distribution is determined by a map (therefore giving valid and invalid regions where the distribution can exist). Methods considered include:

- Maximum Penalized Likelihood Estimate,
- Modified Total Variation MPLE Model,
- a weighted H1 MPLE method (the preferred method),
- and a weighted TV MPLE method.

The H1 MPLE method will be useful for analysis, but does not serve as a foundational basis in the program’s current simulations. However, a very useful concept taken from this paper is the idea of limiting lattice locations; in other words, certain areas are unavailable due to geographical formations (e.g. lakes, mountains, etc.), and thus criminals cannot traverse them, and they contain no houses to burglarize. This will be implemented into the simulation.

The H1 MPLE method can later be utilized in fine-tuning computer simulations such that their results reflect real-world distributions.
2.3 – P. A. Jones et al. (2010)

Statistical Models of Criminal Behavior: The Effects of Law Enforcement Actions

This paper is built upon (2.1 – M. B. Short et al.) by adding a component within a segment in the flowchart of the discrete simulation, as well as extending the previous assumptions of Attractiveness and the inherent dynamic variable. Now, the primary objective is to add law enforcement agents into the equations with the objective of reducing the amount of criminal activity. Several approaches are undertaken, including the following:

- Mapping cops as random walkers – “Unbiased walkers”
- Mapping cops as random walkers on hotspots – “Cops on the dots”
- Mapping cops as random walkers on perimeters of hotspots – “Peripheral interdiction”

Analysis shows that the latter methodology is highly effective at lowering crime, and especially at lowering hotspots. All the methods will be tested in the simulation. Most important, however, is how the paper decides how cops interact with criminals. Two approaches are given in the paper:

- Cops have an effect on the Attractiveness of the site.
- Cops have a certain probability of “scaring” a criminal back home, effectively removing the criminal from the system until the natural spawn rate brings the criminal back.
These two approaches are valid; the first will be integrated into this thesis, though a different method will be added later.

2.4 – P. J. Brantingham & G. Tita (2008)

Offender Mobility and Crime Pattern Formation from First Principles

Papers (2.1) and (2.3) assumed a random generation of criminals given a certain rate of spawning, with the assumption that such spawning could occur anywhere on the lattice grid. This paper addresses the more realistic assumption that offenders and criminals often move locations, and thereby gives basic models that will allow for the simulation of offenders and thus map the crime locations the offender is likely to take. The “minimalist model of offender movement” is that offenders will decide upon a randomized direction as well as a distance to travel each time, given certain parameters.

2.5 – L. E. Cohen & D. Cantor (1981)

Residential Burglary in the United States: Life-Style and Demographic Factors Associated With the Probability of Victimization

This paper analyzes the statistical contributions of certain factors to the probability of victimization concerning residential burglary. The analysis is based on (1975-1976) National Crime Survey data, with special focus on the following factors: age of head of household, area type, income, household occupancy, and race. Most worthy of notice are the concluding Coefficients of Partial Determination (CPD): the paper
concludes that the strongest predictor of burglary victimization is the age of the head of the household (.61), followed by area type (.35), income (.31), household occupancy (.10), and race (.04). Additionally, the paper continues on to further detail the beta effect parameters, which with large samples can be used as a test statistic in a normal distribution:

<table>
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<tr>
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<tr>
<td><strong>Independent Variables</strong></td>
</tr>
<tr>
<td>Income</td>
</tr>
<tr>
<td>$0 - $7,500</td>
</tr>
<tr>
<td>$7,500 - $14,999</td>
</tr>
<tr>
<td>$15,000 - $24,999</td>
</tr>
<tr>
<td>$25,000+</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>16-29</td>
</tr>
<tr>
<td>30-49</td>
</tr>
<tr>
<td>50+</td>
</tr>
<tr>
<td>Race</td>
</tr>
<tr>
<td>Nonwhite</td>
</tr>
<tr>
<td>White</td>
</tr>
<tr>
<td>Major activity</td>
</tr>
<tr>
<td>Less occupied</td>
</tr>
<tr>
<td>More occupied</td>
</tr>
<tr>
<td>Area type</td>
</tr>
<tr>
<td>Central city</td>
</tr>
<tr>
<td>Other</td>
</tr>
</tbody>
</table>

The Beta parameters and the CPD will both be integrated into the final model and program.
This thesis builds upon the foundation laid by the UC MaSC project by introducing a wide variety of new but important factors on top of an independently-programmed simulation. The addition of elements such as non-constant and integrated base attractiveness, maximum burglar steps, geographical information, police-criminal interactions, and new policing patterns, allow the original question to be reanalyzed in a new light, and give further insights on how police can best combat residential burglary. Further details concerning the additional elements, as well as the programming structure and results, can be found in the following sections.
3. Model

The core of this thesis lies in the computer program that both simulates criminal activity and evaluates existing police countermeasures, given certain input sets. This section examines the conceptual framework of the program, while the following section further details the actual programming of the simulator.

The equations and core assumptions provided in A Statistical Model of Criminal Behavior – (M. B. Short et al.) form the basis of the program. In particular, the program adapts the following equations (refer to Literature Review [2.1] for full description) with the relevant aforementioned base assumptions of criminal behavior, under a discrete lattice structure:

\[
A_s(t) \equiv A^0_s + B_s(t),
\]

\[
p_s(t) = 1 - e^{-A_s(t)\delta t}.
\]

\[
q_{s \rightarrow n}(t) = \frac{A_{n}(t)}{A_s(t)},
\]

\[
B_s(t + \delta t) = \left[ (1 - \eta)B_s(t) + \frac{\eta}{Z} \sum_{s' \sim s} B_{s'}(t) \right] (1 - \omega \delta t) + \theta E_s(t),
\]
However, many important changes will be integrated into the new Simulator, and are listed below.

3.1 – Non-constant $A^0$ (and $\Gamma$)

The original paper assumes $A^0$ and $\Gamma$ as constant variables across the board; however, given that most districts have data given the base attractiveness of certain locations (e.g. known incentives for criminals), this assumption is unreasonable, and therefore the new program will be able to take a custom $A^0$ matrix as input. The same applies for $\Gamma$; certain areas with a higher concentration of burglar spawning locations should be treated as such, and thus allows for a matrix input. However, more important is that $A^0$ is now defined and integrated as according to the factors stated in *L. E. Cohen & D. Cantor (1981)*: age of head of household, area type, income, household occupancy, and race. Also included are the varying Beta parameters per factor. This will allow any police force to input given demographic and location statistics to immediately obtain real results.

3.2 – Geographic Information Matrix $X$

The original paper’s simulations also do not take into account geographical barriers and inaccessible sites; as such, the new program will be able to take a custom $X$ boolean lattice as input, which will define the unusable sites in the simulation. This was inspired by the *Improving Density Estimation by Incorporating Spatial Information* – *(L. M. Smith et al.*) paper analyzes difficulties in replicating distributions over real geographic
locations.

3.3 – Maximum Burglar Steps

The original paper’s simulations also assumed that criminal behavior was an infinite random walk, weighted by the attractiveness of the surrounding sites, and ended only by burglary. However, in the real world, though such a random walk is often believed to be reasonable, an infinite one is clearly unreasonable. Real burglars are limited to a constrained time window, and if unsuccessful after a given period of time (e.g. after several hours of fruitless searching, or the nighttime hours), will return and rest for another period of time before attempting again. This will be modeled into the paper as a finite number of maximum steps that each burglar will be assigned. The assumption of what happens to that burglar is given as another input. If the burglar is assumed to return home to his/her origin location (wherever that may have been), the burglar will rest for a set “delay” (which is an input), and then resume operations. If the burglar is assumed to be on a rigid time cycle where he/she would attempt again at the same time regardless of success on a previous attempt (e.g. has a regular cycle of attempting burglaries once a week), then the burglar will be removed from the system and will be allowed to re-spawn through the natural spawn rate $\Gamma$. Note that a delay of infinity is equal to the latter scenario, and that a delay of 0 will instantly teleport the burglar back to his/her starting position and allow the burglar to continue searching for targets.

The initial idea was inspired by Offender Mobility and Crime Pattern Formation from First Principles – (P. J. Brantingham & G. Tita).
3.4 – Police Interactions with Criminals

In Statistical Models of Criminal Behavior: The Effects of Law Enforcement Actions – (P. A. Jones et al.), cops were previously modeled as objects that would either decrease the attractiveness of the site, or one that would with a certain probability “scare” a criminal back to the origin, effectively removing the criminal from the equation until revived with the natural spawn rate $\Gamma$.

However, both these methods are indirect methods of encounter, and do not account for the real-world scenario of direct police-criminal encounters. Namely, in this system, policemen merely act as possible deterrents. It seems much more realistic to assume that policemen act as real interactive beings that also sometimes affect the criminals directly. Namely, the following improvements will be implemented:

- Policemen will act as agents following certain patrol policies (e.g. random walk, “cops on the dots” (Jones), etc.), with a fixed number of agents. This reflects real-world scenarios in which the resources of policemen are limited.
- When a policeman is on a certain site, that site’s Attractiveness will be decreased by a factor. This is akin to the first approach in the Jones paper. A criminal is highly unlikely to burglarize a house with a policeman directly in front.
- However, when a policeman is less than $m$ sites away from a burglary, the policeman will have a probability of capturing the burglar, and thus preventing the burglary and also removing the burglar from the system. Once again, the exponential distribution will be used to model the probabilities, with the independent variable being the absolute distance $x$ between the burglar and a
policeman within $m$ sites.

$$p_{s}^{\text{capture}} = \sum_{\text{cops within } m} 1 - e^{-\mu x}$$

Note that under this system, the probabilities stack, which reflects the desired result; two policemen nearby a criminal have a higher chance of capturing the burglar than one policeman alone. As such, with the aforementioned probability, the closest policeman can catch the burglar and remove the burglar from the system, and this would not register as a successful burglary; otherwise, the burglar will escape.

3.5 – Policing Patterns

As stated in the previous point, Policemen can follow certain patterns to combat crime. The Jones paper states that when policemen patrol the perimeter of hotspots, the diffusion of hotspots is more significant than in other methods, and that criminal activity is lowered to a minimum. However, this method may not necessarily be the best case scenario under the new proposed methodology of police interactions with criminals. As a result, police patterns must be retested in order to find the optimal patterns. The complete list of testable policies includes:

1. The basic random walk. This is mentioned and tested in the *P. A. Jones et al. (2009)*, and will be a good control test. This policy will be called “randomCop”
2. Policemen moving as criminals (e.g. policemen will imitate criminals exactly and move based on a random walk of perceived Attractiveness). This also may test the movement of undercover or unmarked police cars, which is a prevalent strategy in many cities. This policy will be named “burglarCop”.

3. Policemen moving directly towards areas of higher attractiveness. This is a slightly more realistic strategy where policemen make a beeline for the highest attractive spot in the area. This is one of the policies mentioned in P. A. Jones et Al. (2009), and thus shall be named “dotCop”.

4. Policemen moving based on previous burglaries. This is an obvious strategy implemented in the real world: where there are more actual burglaries, policemen are sent to patrol. This method would likely be utilized when policemen do not understand the true Attractiveness of sites. This shall be named “pastCop”.

5. Policemen moving based on set formations. For example, teams of police cars may sweep a large area quickly instead of one patrol car patrolling a large area over a longer period of time. This method has a lot of flexibility, and several different ideas will be tested (e.g. spirals, horizontal lines, loops). One of the patterns tested are rectangular patrols in certain areas: this policy is named “patrolCop”.

6. Policemen moving based on “peripherals” – another policy implemented by P. A. Jones et al. (2009), where it was stated to be the best of the three tested methods in the paper. This will be tested in this thesis’ new system alongside more policies. This policy is named “peripheralCop”.


4. Programming

4.1 – Framework

The primary program behind the thesis utilizes Java Programming as its language. The reasons for doing so are as follows:

- Java is a universally accepted coding platform implementable on many consumer-grade computers, and such, this program can be distributed and utilized very easily with no required additional software (unlike Matlab, R, S-Plus, etc.). Moreover, due to its accessibility and understandability, additional code can be integrated in future projects with relative ease. As one of the goals of this project is to create a program that can also be used by virtually any police force in the nation, Java is a good choice for mobility and usability.

- Java is not version-dependent, unlike software like R. As such, mobility is further increased and the tools required to maintain Java are minimal.

- Java is faster than most heavy-duty software like Matlab. There are faster languages (e.g. C); however, the object-orientated perspective of Java fits exactly with the requirements of this thesis. Policemen and criminals are both treated as objects, and each simulated can be considered an object in itself. This allows for clear coding, modular programs, and easy alterations to the code.

- If help is required, help in Java is abundant online and in the community, while help in other languages is not as available.
The only external program utilized in the programming section of this thesis is Matlab, but Matlab is used minimally and only for its graphing prowess, as Matlab has many aesthetically well-made plotting functions that suit this thesis. Output from the Java simulator is exported to a text file, which is then read by a short Matlab script and printed into a presentable graph.

The main data structure used in this thesis is a set, for which the Princeton University Computer Science department freely provides their own version “SET.java” through Princeton’s Computer Science courses as well as online. “SET.java” is a simple program built upon Java’s TreeSet data structure. “SET.java” also happens to be the only external code utilized in this thesis; all other code is directly coded by the author of this thesis.

4.2 – Programs, Classes & Objects

There are four programs utilized in the simulation: Simulation.java, Thief.java, Cop.java, and SET.java (provided by Princeton University CS Department).

Simulation.java

This Java program makes up the central portion of the thesis. The program itself is designed to simulate dynamic burglar and police activity over time; as such, there exists one main cycle which is repeated (in a loop) over the time specified for the simulation. This cycle and inner loops will be fully explained in the following section (4.3). A summary of functions in Simulation.java is outlined in Appendix A.
Thief.java & Cop.java

The Thief class is a simple object that contains data about the thief’s present location, origin, remaining steps (if actively moving), original maximum number of steps, remaining delay (if inactive due to resting), and original maximum delay. The Cop class is a simpler object; it contains data on the cop’s present location, origin, remaining delay (if inactive due to capturing a burglar), and original maximum delay. A summary of functions in Thief.java is outlined in Appendix B.

4.3 – Conceptual Stages

The initial UC MaSC program, as presented in M. B. Short et al. (2008), was structured in the following basic method:

Figure 4.3.1 – Original UC MaSC Programming Cycle (M. B. Short et al.)
Note that each cycle of the entire program represents one cycle per $\delta t$, and thus the entire program is a loop of the above cycle; moreover, the “criminal loop” represents a nested loop that iterates through all the criminals. Significant changes are made to this model:

4.3.1 – Non-constant $A^0$

As $A^0$ is defined before the loops of the program begin, its addition in the graph is simple:

![Diagram showing programming stages with $A^0$](image)

Calculations of $A^0$ are a bit more complicated; the Beta parameters as defined previously will be distributed normally and then weighted. As such, input matrices for age of head of household, area type, income, household occupancy, and race will be included, which will result in a specified $A^0$ before the loops begin.
4.3.2 – Geographic Information Matrix X

While X is also specified before the loops, the difference lies within the loop itself. The probabilities of moving for burglars (and later, for cops), for example, must check whether the adjacent sites are “open” before checking. Additionally, sites where X defines is unavailable must have a site attractiveness equal to 0. However, the stages of the loop themselves do not significantly change in this step, but will be included in the next step’s diagram.

4.3.3 – Maximum Burglar Steps

As previously stated, to add a dimension of realism, variables for the maximum number of steps as well as for the delay (for burglars to become re-active) become integrated, reflecting the burglar’s human need to stop trying to burglarize past a certain point in time (e.g. after a full night of aimless searching), as well as the time required until the burglar can resume activities and become active again. This severely complicates the burglar loop, as can be seen below. Note that certain changes have been added regarding the X geography matrix.
4.3.4 – Police Interactions with Criminals

The above simply mentions the complex patterns of burglar movements. However, now policemen will be introduced with police-criminal interactions. A new loop, the “cop loop”, is formed, and the complicated resulting system is displayed below.

Note: $K(x,y)$ now represents the probability of capture at each location on the grid.
4.3.5 – Policing Patterns

The final step is to add police patterns into the cycles. Though the above graph seems complete, it is missing the vital component of telling cops how to move. This is done by policy selection; based on user input (defined as an input String in Simulator.java), the policy will be selected before the cop loop. Thus, it is integrated into our cycle as follows:
The above structure reflects the summarized version of the Simulator.java program. The results of the program will be presented in the following sections.
5. Basic Simulation Tests

5.1 – Basic Hotspot Formation

The program must first confirm the basic scenario. *M. B. Short et al. (2008)* showed that three outcomes can occur in their simulation when considering the attractiveness matrices: stationary hotspot formation, dynamic hotspot formation, and no hotspot formation. The ideal scenario is to have stationary hotspot formation to reflect real criminal hotspots. Using the program with no policemen (as in *M. B. Short et al. (2008)*) and with the most basic assumptions (constant $A^0$, unlimited burglar movement, fully open geography, constant $\Gamma$, etc.), this result can be replicated and achieved:

**Figure 5.1.1 – Basic Hotspot Formations in Attractiveness Matrix $A$**

\[
t = 50, \ dt = 1/100, \ \omega = 1/10, \ A^0 = 1/30, \ \eta = 0.03, \ \theta = 0.56, \ \Gamma = 0.002
\]
5.2 – Maximum Steps/Time

However, with the introduction of all the aforementioned new elements, this hotspot formation is likely to change. First, criminal activity per trip will be limited to a maximum of 65 steps, or ‘site movements’; in other words, a criminal will go home after moving 65 sites, and wait until another time to try again. This is referring to section 3.3 of this thesis. Thus, the following formation is obtained:

**Figure 5.2.1 – Limited Criminal Movement Distance in Attractiveness Matrix A**

\[ t = 50, \, dt = 1/100, \, \omega = 1/10, \, A^0 = 1/30, \, \eta = 0.03, \, \theta = 0.56, \, \Gamma = 0.002 \]

As expected, some of these hotspot formations have disappeared, yet some remain. This is logical because if criminals were heavily restricted to their origins (e.g. maximum criminal activity of 10 steps per trip), site attractiveness (given assumption of constant \( A^0 \)) would be relatively constant across the grid, and no hotspots would ever form. As such, the result obtained above represents the approximate borderline where hotspots are still
forming with the realistic condition of limited criminal movement time. For example, assuming a maximum of 20 steps, the attractiveness matrix is as below:

**Figure 5.2.2 – Highly Limited Criminal Movement Time in Attractiveness Matrix A**

\[
t = 50, \ dt = 1/100, \ \omega = 1/10, \ A^0 = 1/30, \ \eta = 0.03, \ \theta = 0.56, \ \Gamma = 0.002
\]

As such, the maximum steps (or time) imposed on a burglar’s criminal activity (per trip) has an obvious effect that negates hotspots if the maximum steps are too few (or time is too short). Thus, a reasonable medium of 65 steps (roughly translated to slightly over half a day) will be utilized throughout the remainder of this thesis in order to ensure realistic conditions.

### 5.3 – Police Interactions

Additionally, it must be tested whether policemen have the desired effect on capturing criminals. To test, a large number of cops (for example, 50) will be introduced into a basic simulation with a basic policy (“randomCop”, where cops will take random
walks), and the number of criminals captured will be recorded. The results are shown below:

**Figure 5.3.1 – Highly Limited Criminal Movement Time in Attractiveness Matrix A**

\[ t = 50, \, dt = 1/100, \, \omega = 1/10, \, A^0 = 1/30, \, \eta = 0.03, \, \theta = 0.56, \, \Gamma = 0.002 \]

Captures: 22

As seen, the introduction of an enormous number of policemen into the system has the desired effect upon criminals; criminals are captured, and attractiveness is decimated across the grid. Thus, the simulated cops are working as expected.
6. Results & Analysis

6.1 – Simulation Plan

There exist several permutations of variables to utilize the tools created in the previous sections. In order to find the most effective methods, the following variables will need to be tested:

- **$A^0$: constant, randomized, gradient hotspot**
  
  Base attractiveness can be assumed constant throughout the grid, randomized per site according to the previously mentioned factors (age of head of household, area type, income, household occupancy, and race), or simulated in “gradient hotspots”, where the aforementioned factors are clustered in order to simulate real-life situations.

- **$X$: open, randomized, clusters**
  
  Similarly, geography can be either completely open with every lattice being accessible, randomized per site, or done in clusters to simulate real clumps of inaccessible areas (e.g. a pond, lake, cliff, mountain, etc.).

- **Policy: “randomCop”, “burglarCop”, “dotCop”, “pastCop”, “patrolCop”, “peripheralCop”**
  
  The different policies mentioned earlier in this thesis will also be tested in order to determine their effectiveness.
Now, a metric must be defined that can, to some degree, measure effectiveness of policemen and their policies upon differing settings of $A^0$ and $X$. It would be ideal for the community for the number of burglars captured to increase, while the number of total burglaries decreases. As such, both statistics will be measured.

Regarding policemen: the national average of officers per 1,000 inhabitants is 2.3 (Criminal Justice Information Services Division), and the average household size is 2.6 (U.S. Census Bureau). As such, on a 128x128 grid, the average expected number of policemen would be 42.6 policemen. This thesis will therefore use 50 policemen for sanity’s sake, and thus 50 cops will be introduced into our system, with their initial placements being randomly distributed across available spaces on the grid; tests have shown that the number of policemen and their initial positions, on average, change little regarding the relationships between policies. Finally, the simulations will be run multiple times in order to establish stable average values for our results.

### 6.2 – Summary of Simulation Results

Each simulation with a corresponding policy was run five times in order to obtain a safe average for each combination. The inputs remain the same as before:

$$t = 50, \Delta t = 1/100, \omega = 1/10, A^0 = 1/30, \eta = 0.03, \theta = 0.56, \Gamma = 0.002$$

The table is given below is a compilation of the averages for Police Captures as well as Burglaries Committed across varying $X$, $A^0$, and policy. Each number point represents a separate simulation.
6.3 – Pre-Analysis of Results

There are certain things that stand out instantly from a glance of the above table.

The first obvious noteworthy point is that the number of police captures seems quite low compared to the number of burglaries. This can be attributed partially to the input for $\mu$ (the constant that helps determine probability of capture), partially to the input for the max radius a policeman can “observe” and catch a criminal any one point in time, and partially to the fact policemen have a delay when transporting the captured criminal.
to a department before they can return to the job. However, upon adjusting the inputs in follow-up tests, the results did not change significantly, and more importantly, the trends and relationships between policies did not change. Moreover, considering how the burglaries were achieved over a time of 50 days, an average of ~25 burglaries a day in a 16,384-site grid seems quite reasonable.

In fact, these numbers are not that surprising, because it accurately demonstrates the realities and limitations that average policemen face. In a real-world system, 50 policemen patrolling 16,384 sites would have difficulty capturing criminals, especially considering how site attractiveness is lowered when a policeman is patrolling it; in other words, criminals will generally avoid policemen and often burglarize when policemen are not nearby, resulting in the low number of captures.

As such, the first immediate takeaway from these results is that policemen patrol policies perhaps should not be established by prioritizing police captures; rather, police departments may desire to focus on lowering the number of burglaries, rather than increasing the number of captures. This is, again, due to the fact that the number of captures is likely to be but a fraction of the number of burglaries. However, in certain cases, a police department may decide otherwise, for reasons that will be explained in the following section.

6.4 – Police Captures Analysis

Though police departments should generally focus on lowering the number of burglaries, there are many reasons for which a police department may rather desire to increase the
number of captures. One reason is the issue of repeat burglars; an individual or group of criminals may be responsible for a multitude of burglaries, and as such may be deemed as a special target. As such, capturing such individuals may immediately and significantly decrease the number of burglaries. Another reason is the awareness and intimidation factor. Fellow burglars, in the real world, may learn of police activity on cracking down on burglars, and as a result may be discouraged from engaging in burglary. Another possible reason is information; these captured burglars may have information on other burglars, burglary sites, or previously stolen items that the police may wish to locate. Therefore, while the average number of police captures may be low, they still present several credible reasons for police departments to pursue a focus on captures.

Thus, the policies to be analyzed are now evaluated with respect to the number of police captures. The relevant excerpt from Figure 6.1 is shown below:

Figure 6.4.1 – Police Captures, excerpt from Figure 6.2.1

<table>
<thead>
<tr>
<th>Policie Captures</th>
<th>open</th>
<th>random</th>
<th>hotspot</th>
<th>constant</th>
<th>random</th>
<th>hotspot</th>
<th>constant</th>
<th>random</th>
<th>hotspot</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>14</td>
<td>16</td>
<td>14</td>
<td>27</td>
<td>29</td>
<td>38</td>
<td>17</td>
<td>19</td>
<td>19</td>
</tr>
<tr>
<td>A0</td>
<td>14</td>
<td>16</td>
<td>14</td>
<td>14</td>
<td>16</td>
<td>14</td>
<td>14</td>
<td>16</td>
<td>14</td>
</tr>
<tr>
<td>randomCop</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>burglarCop</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dotCop</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>pastCop</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>patrolCop</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>peripheralCop</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
There are several trends that are immediately apparent. The first is that, surprisingly, the terrain and geographical formation matrix seems to have very little effect on the number of police captures. Comparing when $X$ is “open”, “random”, and “clusters”, all the policies seem to exhibit similarly increasing values (simply because “open” has more open lattice sites than “random “ or “clusters”), with a few small exceptions. This leads to a possible idea that geography does not theoretically play a large role in the type of policies that police departments should undertake.

Secondly, and equally surprisingly, virtually all the policies with the exception of one policy (“dotCop”) have very similar results. This is shocking because the very first method, “randomCop”, is the method in which policemen all undergo completely random walks. When comparing “randomCop” to “pastCop”, which is one of the more traditional methods of police patrolling policy where policemen tend towards areas of higher past burglaries, while “pastCop” is generally higher across the board, the values are very similar at times. Thankfully, “randomCop” has the lowest total number of captures; however, it begs the question on why the values are so similar. Analyzing this logically, the result may be due to the burglar’s high sensitivity to police with respect to site attractiveness. If directly nearby, policemen will likely scare off burglars even off the more attractive sites, and the burglar will likely move until a site’s attractiveness is too high to resist. In real-world terms, a burglar will likely burglarize a site when there are no police nearby, and may resist burglarizing a high-value location if there is a policeman passing by.

Lastly, while all the other policies have very unspectacular results, “dotCop” produces relatively outstanding numbers, generally averaging around twice the
productivity of the other methods. This is very interesting when considering the real-world applications of this policy. In a “dotCop” policy, a policeman would park himself in the middle of the most attractive sites in the area, and simply wait until either a burglar attempts to break in nearby or the attractiveness of the sites falls. This differs from “burglarCop”, because in the latter policy, a random walk is integrated into the attractiveness sites; in the aforementioned real-world application example, the policeman would simply tend to approach high-attractiveness sites, but would often pass by, allowing a waiting burglar to burglarize after the cop leaves. Another interesting note is that the dotCop policy significantly increases in productivity when there are geographical restrictions on \( X \); this may be because criminals are “funneled” into high-attractiveness areas, where waiting police can pounce on potential burglars.

As such, “dotCop” clearly distinguishes itself as the best policy to undertake if prioritizing the capture of burglars, especially if the geography is restrictive. Additionally, it was found that according to the simulator, traditional methods of “pastCop” (targeting high-burglary areas) and “patrolCop” (taking general patrols) were not very successful, and only marginally better than a completely random walk. Also, though the “peripheralCop” policy described in the P. A. Jones et al. (2009) paper was stated to have a large effect on eliminating criminal hotspots, it did not have a significant effect on the number of police captures.
6.5 – Burglaries Committed Analysis

The above section described policing policies for departments that prioritize captures. However, generally speaking, police departments are likely to care most about the well-being of the general populace, and will focus on lowering the number of overall burglaries committed. In fact, all other results held constant, an increase of captures is often undesirable, as captured criminals cost departments and the government valuable time, money, and if the criminal is sentenced, facility space (i.e. prisons). As such, this section will analyze policies with the objective of lowering the overall number of burglaries.

The relevant excerpt from Figure 6.2.1 is displayed below:

<table>
<thead>
<tr>
<th>Burglaries Committed</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
</tr>
<tr>
<td>---</td>
</tr>
<tr>
<td>open</td>
</tr>
<tr>
<td>random</td>
</tr>
<tr>
<td>hotspot</td>
</tr>
<tr>
<td>random</td>
</tr>
<tr>
<td>random</td>
</tr>
<tr>
<td>hotspot</td>
</tr>
<tr>
<td>clusters</td>
</tr>
<tr>
<td>random</td>
</tr>
<tr>
<td>hotspot</td>
</tr>
</tbody>
</table>

There once again exist several interesting trends. Firstly, somewhat similar to before, while the numbers are very similar when comparing X “open” and X “random”, the X “clusters” data points are on average a bit smaller. This is, once again, likely
partially due to the simple fact that the hotspots severely restrict spaces open for travel and “funnel” all agents down smaller areas, leading to fewer overall burglaries.

Secondly, it is a surprise to see that “dotCop”, “pastCop”, “patrolCop”, and “peripheralCop” all have a very similar range of numbers. Despite the clearly strong performance of “dotCop” in capturing criminals, it is apparently not as robust in lowering overall sites. Additionally, the “peripheralCop” policy that was expected to lower hotspot formations once again did not stand out; there was no significant difference between all four of these policies. Analysis on exactly why will be conducted later in this section.

The last point worth mentioning is definitely the most surprising; the best-performing policy with respect to total burglaries committed was “burglarCop”, followed extremely closely by “randomCop”. These two policies generally outperformed the other four policies by an average of over 10%. It is especially surprising to see that the simulation states that a policy of random walks performs better in reducing overall burglary rates than several highly specialized methods such as “dotCop” and “peripheralCop”, as well as older traditional methods such as “pastCop” and “patrolCop”. It is heartening to see, however, that “burglarCop” often performed better than “randomCop”, although it was only by a slim margin. So what exactly was the problem of the other four methods, and why did the top two perform as well as they did?

Upon further analysis, the answer is simple but different for each of these policies; all of the four methods have weaknesses that undermine their practicality in the real world.
The first weakness applies to both “dotCop” and “pastCop”: the problem lies in “clumping”. Upon further analysis of the movements of policemen, it was noticeable that policemen began moving straight for the areas of higher desirability, whether it was for higher attractiveness (“dotCop”) or higher burglary rates (“pastCop”). Unfortunately, often times, these areas of higher attractiveness and higher burglary rates were targeted by more than one policeman; sometimes, many policemen would be drawn together and form a “clump” around an area of high attractiveness. An explanatory example is displayed in Figure 6.5.2 below:

**Figure 6.5.2 – “Clumping” with Strict Movement Policies**

What is interesting is that policemen would clump together towards areas of higher attractiveness (or higher burglar rates, if discussing “pastCop”), which would deter burglaries in the area; however, since their effective coverage of area had decreased due to their clumping, the number of burglaries in other areas would increase, which would then shift the dynamic portion of site attractiveness (as well as burglary rates), effectively changing the balance of the grid again. As a result, through both the “dotCop” and
“pastCop” policies, policemen were essentially creating more unguarded areas than when compared to a random policy such as “randomCop”, which by its very nature, would spread out policemen across the grid.

The second weakness applies to both “patrolCop” and “peripheralCop”. Upon further analysis of burglary locations, it seems that the problem is actually the inverse of the previous problem mentioned in “dotCop” and “pastCop”. The issue here lies in the policies’ desire to stay a relatively fixed path. Figure 6.5.3 further explains the problem in the case of “peripheralCop”:

![Figure 6.5.3 – “Circling” with Strict Path Policies](image)

The issue here lies in the problem of the “peripheralCop” policy’s attempt to circle areas of high attractiveness. The objective of the policy is to locate hotspots, and
through encircling their peripheral areas, eliminate hotspots by lessening the dynamic portion of attractiveness. However, though the hotspots may fade, due to its unwillingness to venture into areas of high attractiveness while not straying too far from its desired pattern, it seems that the policy has difficulty on both capturing criminals and also lessening overall burglaries.

The issue is magnified with “patrolCop”. No matter the patrol route of the cop, the areas that are not patrolled become hotspots for burglaries. Additionally, if assuming a patrol policy, the police department must either sacrifice coverage or time; if the policeman is thorough, many sites may be visited, but length of time between visits is significantly longer, which allows for a time window for burglaries. As a result, “patrolCop” struggles with the objectives due to its strict adherence to a single path.

Thus a conclusion is found that these highly strict and specialized policies often find difficulty from the very nature of their adherence to their rules. In this simulation, a randomized element clearly has a strong effect in lowering burglaries. The difference is clear when comparing “dotCop” with “burglarCop”; the two methodologies are extremely similar, but “burglarCop” adds the randomized walk element alongside its analysis of high attractiveness sites, and produces the best result of the six tested methods. It is therefore found that according to this simulation, a random element in policing strategy is highly effective in lowering burglary rates, and strict policies suffer under the very nature of their rules. Additionally, if a recommendation must be made for the best policy, “burglarCop” outperforms “randomCop” not only in simulation, but in real life; a true police force, assuming that the attractiveness values are accurate, could utilize this information and increase their efficiency.
7. FURTHER DISCUSSION

7.1 – Limitations

The simulation and modeling of real-life human interactions will always have many limitations, most important of which are usually the base assumptions of the model. This model assumes burglars to be purely extrinsically motivated by a site’s base attractiveness (compiled from census statistics) as well as a dynamic component; however, this model does not take into account the burglar’s own origins, motivations, and actions. Such a model, however, would require a much deeper understanding of criminology, psychology, and history that was not fully realizable in the short time span of this individual thesis. Likewise, there exist several other base assumptions that are questionable; for example, the assumption that police and criminals move at equal paces is another issue that separates the theoretical results from reality. In short, while the assumptions have solid logical and statistical reasoning behind them, they are unlikely to be sufficient to model real-world interactions accurately.

Another important limitation is time. The simulations were completed upon a small grid with a relatively short maximum time frame; however, even so, individual simulations often took hours on high-performance computers. As such, significantly larger tests should be completed in order to increase accuracy and reliability of the results.
Additionally, the policing policy is a crucial limitation. This thesis has only tested six basic policies; however, the possibilities are significantly greater and these results may differ with different policies.

And though there are more limitations, the last important limitation mentioned here are the yet-unknown external factors. As stated before, simulation remains theoretical unless all the important factors are accounted for; however, it is difficult to know positively when all have been accounted for. The only partial solution to this problem is repeated testing.

7.2 – Recommendations for Future Work

Naturally, the aforementioned limitations are also recommendations for future work on this project. The base assumptions should be revisited and expanded upon; most interesting is likely the methods of movement of policemen and burglars, as well as learning more about the burglar. Significant amounts of simulation time on faster computers should be spared in order to absolutely guarantee results. New policies should be invented and tested, and external factors should be further researched in order to make the simulator more viable.

However, on top of all this, there exist other important recommendations for future work.

The most important of which is real-world application and testing. The next step after creating a very strong simulator is to apply the simulator to a test area and gauging
the results. This would have to integrate a high level of geography input, as well as traffic routes and building locations; as such, it is both data-intensive and time-intensive. Working with other departments would help bring expertise from areas such as criminology, mathematics, psychology, and computer science. The overall objective of this stage would be to build a working prototype for a system that advises each officer in a precinct on where to police.

An interesting component to add to the simulator would be the idea of repeat burglars. If these burglars could be modeled, then using this information, police may be able to capture these burglars at subsequent break-in attempts. This could allow police to focus on high-value targets. Another interesting component would be to include alarmed houses; often times, these alarmed houses will contact the alarm company that then automatically contacts the police. This could change the attractiveness model, as burglars would have a chance of breaking into a house and fleeing simply from the alarm, or perhaps be less inclined to target neighborhoods with many alarmed houses.

Lastly, the final step would be to expand the simulator from just residential burglary to crime in general. Doing so would require a complete overhaul to the basic assumptions of crime, and each type of crime must be modeled differently according to their own assumptions. However, accomplishing this final stage could assist police departments across the world.
This paper has used an expanded simulator to test both traditional and nontraditional methods of policing for residential burglary, and the results hold potential significance for every policing agency and department. Regarding maximizing police capture rates: analysis has shown that a policy that directs police agents to areas of higher site attractiveness is significantly more effective than the other policies tested in this thesis. Moreover, this effect is increased in areas with geographical limitations, as the geography serves to force all agents into closer interactions. Assuming a non-constant base attractiveness attribute for sites and utilizing the natural grouping tendencies for site attributes also assists in the efficiency of the aforementioned policy. Regarding minimizing overall burglary rates: analysis has shown that a policy that integrates a randomized component into the policing routes perform significantly better than policies that adhere to strictly defined patrols or rules. Additionally, this effect is also increased in areas with geographical limitations and non-constant base attractiveness attributes, for similar reasons as stated previously.

Furthermore, the simulation behind the paper has heavily built upon the foundation set by the UC MaSC project and affiliates. The addition of non-constant and integrated base attractiveness, maximum burglar steps, geographical information, police-criminal interactions, and new policing patterns serve to create a simulation that better resembles real-world criminal and police activity. As such, the simulation and model behind the simulation comprise the next stage upon which further work can be done.
This paper concludes by stating project limitations and offering recommendations on next steps; with additional input from differing departments and viewpoints, a simulation that truly reflects the residential burglary scene, and perhaps also the general crime scene, may just be possible to achieve.
Appendix A — Simulator.java Summary

Outlined below are the instance variables and basic functions for Simulator.java.

```java
import java.io.FileNotFoundException;
import java.io.FileOutputStream;
import java.io.PrintStream;
import java.util.Iterator;
import java.lang.Integer;
public class Simulator {

    // instance variables
    private SET<Thief> T; // set of Thieves
    private SET<Cop> C; // set of Cops
    private int[][] Z; // Total number of burglaries
    private int[][] E; // Number of marginal burglaries
    private int[][] F; // Number of captures by police
    private double[][] P; // prob burglary
    private double[][] K; // prob capture by police
    private double[][] R; // prob criminal spawn
    private double[][] A0; // base attractiveness
    private double[][] B; // dynamic attractiveness
    private double[][] A; // attractiveness
    private boolean[][] X; // lattice availability
    private int[][] CLoc; // location of cops
    private double theta; // theta for dynamic attractiveness
    private double eta; // eta for dynamic attractiveness
    private double omega; // omega for dynamic attractiveness
    private double totalt; // total time
    private double dt; // dt
    private double delay; // delay for tired crook to resume at home
    private double cdelay; // delay for busy cop to come back to spot
    private int maxsteps; // max steps per thief
    private double avoidr; // % of decrease of dynamic comp when cop present
    private int cdist; // # steps away for max capture dist (0 = no capt)
    private double mu; // multiplicative factor for exponential capture
    private String policy; // policy for cop patrolling
    private int coptotal; // # of total cops

    // constructor
    public Simulator(boolean[][] X, double[][] A0, double[][] R,
                     double theta, double eta, double omega,
                     double totalt, double dt,
                     double delay, double cdelay,
                     int maxsteps,
                     double avoidr, int cdist, double mu,
                     String cspawn, String policy, int coptotal) {
    }

    // add thief to SET of thieves, given starting location, max steps for thief, and an override boolean
    public void addThief(int x0, int y0, int maxsteps, boolean override)
```

53
// add cop to SET of cops, given starting location
public void addCop(int x0, int y0)

// adding all initial cops, given placement policy format
public void addInitCops(String s)

// update P array (probability of burglaries)
public void updateP()

// update K array (probability of capture by police), given cop location
public void updateK(int xi, int yi)

// un-update K array (probability of capture by police), given cop location –
// utilized when police are busy
public void unupdateK(int xi, int yi)

// update both A and B arrays (attractiveness arrays)
public void updateAB()

// move a cop in the (+x,+y) direction
public void moveCop(Cop cop, int x, int y)

// determine closest cop – utilized when burglar is being caught
public Cop closestCop(int x, int y)

// loop of burglar
public void burglarLoop()

// loop of cop
public void copLoop()

// Main Loop
public void run()
Appendix B — Thief.java Summary

Outlined below are the instance variables and basic functions for Thief.java.

```java
public class Thief implements Comparable<Thief> {
    // steps represents the number of steps left, steps0 the original max steps
    public int x, y, x0, y0, steps0, steps;
    // dcount represents the delay count, dcount0 the original max delay
    public int dcount0, dcount;

    // Thief constructor - adds to pos (x,y)
    public Thief(int x0, int y0, int max, int dcount)

    // compareTo function
    public int compareTo(Thief o)

    // moves thief (+dx, +dy)
    public void move(int dx, int dy)

    // resets thief to original position, sets delay back to normal
    public void reset()

    // decrements delay on thief (inactive status)
    public void decrementDelay()

    // decrements steps on thief (active status)
    public void decrementSteps()
}
```


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