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Term Project/Paper

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Abstract

Agent based models of criminal behavior often focus on the negative aspects that lead to increased criminal activity in the artificial communities, such as gang presence or potential policing strategies. Others focus on some factors involving group formation or schooling. This model compiles a number of these and attempts to dock these with some of the prevalent theories from criminology.

Introduction

This paper will construct an exploratory model for the analysis of different potential theoretical social structures affecting crime rates and variances. It's intent is not to develop a new theory for analysis of crime or agent based modeling, but to compile some of the existing structures to determine some of the competing effects. First, the paper will examine some of the work done in the field, and then describe an agent-based model that draws from the existing field, followed by an analysis of some of the experimental results the model yielded. Finally, the paper will address some of the concerns and speak to potential future work.

Related Work

This paper and project will examine the effect of social and group dynamics on rates of crime within and among municipalities. Much work has already focused on many aspects of crime and scores of models, both agent-based and others involving geospatial, socio-economic, and other types of relations have been developed. This paper provides a brief survey of a few papers that, though all agent-based, tackle the problem from different perspectives. While Glaesar et al approaches crime patterns through the lens of social interaction on a lattice, Berry et al uses positive influence models to emphasize the role of gang recruitment. Epstein also maps recruitment and socially meted activation, but through the lens of civil violence, while Huddleston et al adds features of the spatial arena to better understand the social interaction. Each is concerned with how violent behavior spreads or is localized over time, what responses authorities undertake to combat it, and the effects of group and individual behavior on the macroscopic crime trends. After discussing these papers and the features most salient to this project, this paper will propose a model that draws from the models to create a new model that will examine the issue of social and group dynamics of crime from yet a another slightly different perspective, involving social influence and group dynamics.

The model depicted by Berry, Ko, Lee, Moy, Pickett, Smrcka, Turnley & Wu, is perhaps the most simple of those surveyed, and was used to examine group recruitment [Berry et al]. The paper set out to model the recruitment of at-risk youth to gangs in inner cities. To do this, they utilize a two level model [Berry et al, 13] whereby the agents, here adolescent males, interact both with each other and with abstract agents on a second level which represent agent groupings (school, gang) that are "more than the sum of their parts" [Berry et al, 13]. The adolescent agents are defined by three attributes, two of which are not explicitly defined but meant to exploit homophily among agents. The third attribute marks a tendency to attend school, set to either "low" or "high". This tendency towards attendance or truancy is used to separate the agents and expose them to different stimuli: the agents attending school cannot interact with the gangs, who are only (in this model) active outside the school environment, and vice versa. The abstracted school agent is a metaphor; it is meant to be an aggregation of positive influences that those who have a high tendency to attend school are subject to, steering those agents away from gang recruitment. Additionally, agents have a propensity to join, and dissuade or persuade other agents to join gangs, here called the "Gang-Index."[Berry et al, 16]

The model studied the effect of network or interaction density on gang growth and determined that for higher interaction densities, above 16%, eventually all agents, even those with a high tendency to attend school will be recruited into gang life. While certainly showing that there is a connection between gang life and social connected, this finding seems problematic: the system reached equilibrium with complete gang coverage, a situation that seems unlikely to occur in any real world community. The study does acknowledge its lack of investigation on the density of social networks occurring in these locations like those modeled [Berry et al, 33]. Unfortunately, this makes it difficult to measure the model's fit to reality. Further, while interesting and novel, the aggregate school agent as a wholly positive influence seems to be a weakness of the model. While it works as a metaphor, the inner city schools are very likely not free of gang influence, nor are they wholly positive environments for the at-risk youth who attend.

These problems aside, the focus on social networks of actors in crime and gang recruitment is highly intuitive and a strength of the model; gang existence outside the influence of these networks seems highly unlikely.

Joshua Epstein's paper modeling civil violence proved to be a simple, elegant agent-based model that examined the forces that promote and discourage recruitment to non-state causes. His model refined the first cited model's approach by introducing risk aversion in his agents. The primary agents, potential revolutionaries, were drawn from a uniform distribution of risk-aversion concerning being caught and jailed. Two other parameters were present: an agent's perceived sense of hardship and the legitimacy of a state's central authority [Epstein, 7234]. Taken together, these marked an agent's propensity toward anti-state or revolutionary action. The potential revolutionaries are distributed on scales of their attributes, so that some will be more aggrieved than others, and some will be less risk averse. Those who "go active" agitate others potential revolutionaries to do the same. Epstein introduced a second agent type to combat the potential revolutionaries, an authority figure known here as a cop. These agents simply checks their local neighborhood for rebellious actors and, if found, arrests them. The potential revolutionary agents measure the likelihood that they'll be caught based on the presence or absence of cops as a function of agitators in their neighborhood, along with their risk aversion and level of agitation to determine whether or not to join their rebellious neighbors.

This model exhibited several interesting behaviors of the agents. Epstein found that the agents engaged in "deceptive behavior", appearing non-rebellious when a cop was in their presence and turning revolutionary as soon as the cop left their neighborhood [Epstein, 7245]. This is important outside of the arena of civil disobedience Epstein modeled, as gang members and criminals may be able to be blend in when not engaged in criminal activity, or indeed even while they are engaged in criminal activity. Another interesting phenomenon emerged when the regime was subject to a quick drop in perceived legitimacy – the spread of newly aggrieved revolutionary agents quickly overwhelmed the central authorities power to contain them. This revolt occurred at an overall higher level of legitimacy than when the central authority was subject to a slow decline in perceived legitimacy, indicating that potential revolutionaries can do much more harm to the apparatus of the state through a well timed push of bad press than through many small grievances over time, as the latter allows the police to pick off the small number of new agitators before they can accumulate and foment rebellion on a massive scale [Epstein, 7247].

Epstein's police officers resemble the coalition forces in Huddleston, Learmonth, and Fox's model examining the behavior of non-state actors and the responses of those in the employ of the state. This paper employs conception of place more deliberately than the other models, by applying a technique employed by crime analysts to focus deployment of officers called "situational crime prevention"[Huddleston et al, 255]. This technique of enforcement is based on the idea of "feature space modeling," using geospatially keyed data and focusing enforcement "on certain key areas, protecting the populace and bring stability to a location, then allowing that sense of calm to spread" [Huddleston et al, 256]. To illustrate, they consider the likelihood of an incident like a robbery is based on a match between the preferences of the offender and the characteristics of the target [Huddleston et al, 256], notably including the absence of authority. These preferences are estimated based on a number of characteristics, then plotted geospatially. Using this plot, the study found that authority agents placed on the map in areas with a high probability of incident produces the most dramatic drops in incident rates and increases in perceived protection of the populace. The model authors note, however, that they did not examine recruitment or other environmental variables such as quality of life indicators.

Like Huddleston, the final model surveyed is also heavily concerned with place, and the large variance in crime between locations, authored by Glaeser, Sacerdote, and Scheinkman. The authors showed that the variance in crime data between locations cannot be explained by quality of life or location-based indicators alone and design a model based on social interaction to account for it. The model places agents (citizens) on a lattice where their decisions about whether or not to engage in crime can potentially be influenced by their lattice neighbors' decisions about crime [Glaeser et al, 508]. The agents are divided into three types, diehard law citizens, intransigent law breakers and a third class that will be swayed by their neighbors decisions [Glaeser et al, 514].

The study spent significant effort attempting to isolate the variable of social interaction by analyzing the empirical data and deriving statistically what other confounding variables might be in play in determining a variations in a city or precinct's crime rate, as well as how the variables that may contribute to variances in interaction that exist between cities. The paper concluded that the cross-city variance in crime rates is very high to be the outcome of criminals making independent decisions to engage in criminal activity, and that evidence of covariance across agents exists [Glaeser et al, 542]; suggesting that criminals make decisions to engage dependent on others. Also interesting, the empirical study found that crimes committed by younger criminals have more social interaction. While the study considered many other variables as candidates contributing to the variance, crime is too complicated a social phenomenon to come to any solid conclusions as to cause – there are simply too many different possibilities to test them all, especially for multivariate candidates. While this may be construed as a weakness of the model, it is not a major one and has less bearing on the working of the agent based model than it does on the model's potential fit with the world. While this is certainly a critical metric, it does not necessarily invalidate the model.

Model Description

Conceptual Model

Each of the models discussed brings an interesting perspective to how social behavior and crime may interact. This model borrows elements of a few of them, to model how group dynamics might affect crime rates. The studies surveyed note the presence of social influence, interaction, and enforcement strategies in crime rates. Others model processes that may be at play in gang formation. This paper contends that holding all else constant, it is likely that activity and social influence, both negative and positive, may account for some significant portion of the variance between crime rates in different locations and times. To determine this, this exploratory study alters a number of micro and macro level parameters to attempt to see their affect on the crime rate as well as both spatial and temporal variance in the crime rate.

The hope is to gain an understanding of how both community action teams (like neighborhood watches) and gangs affect the crime rate for a local community. This differs from the other studies in that it attempts to capture not only negative influence, but also the positive influences that exist and influence behavior. It also differs importantly from the Glaeser et al study in that it hopes to capture not only social influence of individual actors on their network neighbors, but also in-group dynamics of mutual reinforcement on their decisions. It differs from the Epstein and Huddleston studies by adding group behavior to the enforcers as well as those they would hope to control.

The model also examines the mutual reinforcement of action through groups of like-minded individuals. Here, the scoundrels and the citizens are influenced by not only seeing other, similar individuals around, but more so if the agents are actively engaged with the environment. A citizen, for instance, coming across another citizen who is engaged in cleaning up the environment will be a small percent more likely to become engaged. These groups will work to mutually reinforce each other toward their goals; the citizens will be more inclined towards cleaning up the crime, the scoundrels will be more inclined toward committing a crime. This aims to estimate both the recalcitrance of crime in communities with gangs and the converse, the reduction in a neighborhood's crime from a citizenry involved in awareness and enforcement.

Implementation of Conceptual Model

This model is constructed of a simplified environment where two types of agents, citizens and scoundrels are present. The scoundrels, according to their confidence in their ability to get away with it, place crime (here, a nugget of crime) in the world.

Citizens

The citizens move randomly in a 2D grid. At each step, they make a number of calculations. The citizens are born with a bravado ratio, which is normally distributed throughout the agents (users can set the mean, standard deviation) between 0 and 1. This level is meant to be a metaphor for the predilection toward taking risk and action to address problems in their environment. If their bravado level is above the action limit level (user settable), they will act on crime they come across. This is a metaphor – perhaps the citizens call their local representative to have some graffiti cleaned up, or call the police when they see a crime, or participate in other neighborhood activities that reduce crime rates. This action, however, is not without cost and the agents who engage in this activity experience a drop in their level of bravado after encountering crime (user settable). This is obviously a vast oversimplification, as many of the activities mentioned may actually strengthen an individual's commitment to "fight crime". That said, the strengthening affect is incorporated in the model, achieved through an alternate method. As the citizens wander the grid, they also encounter other citizens. Each time they see others in their neighborhood, their sense of bravado is slightly incremented (user-set). Conversely, if the citizens do not see any other citizens around, their sense of bravado will decrement slightly (user settable). For simplicity, the citizens' interactions with criminals currently have no affect on the citizens.

Scoundrels

Like the Citizens, the scoundrels move randomly on a 2D grid, make a number of calculations at each step, and have an inborn, normally distributed bravado ratio. The bravado ratio here also represents a predilection toward taking risks and action on their environment. However, for the scoundrels, this rate represents a predilection toward the opposite kind of behavior, and the environment's affects on it are different. There are three main environmental parameters that affect the scoundrel's bravado rate. The first is the surveillance effect: as scoundrels wander, they take account of whether or not they see citizens around them. When they see a citizen their propensity to commit crime, as embodied in their bravado rate, drops slightly. If on the other hand they do not see any citizens, their confidence increases slightly. This is meant to model the propensity of crime to happen when people are not watching, and the casual surveillance affects dampening of crime rates {citation}. An opposite affect occurs when the scoundrels see crime or fellow scoundrels – they become more confident that neither crime nor criminals are dealt with, and that they can get away with it. For purposes of simplicity, we are estimating that scoundrels will be approximately 10% of population of the citizens, e.g., if there are 50 citizens there will be 5 scoundrels.

The model adds one final parameter to test the increase in propensity to become involved if an agent sees others involved. For instance, this if a citizen encounters another citizen engaged in crime prevention, they are more likely to become involved in crime prevention (this is separate from the propensity increase they experience if they another citizen not engaged in crime prevention). Similarly, if a scoundrel sees another scoundrel engaged in devious behavior, they may be more likely to engage in such themselves. For the sake of simplicity, the effects of involvement is set at one value for both types of agents: if an agent encounters another agent of their type engaged with their environment, the affect is the same percentage increase regardless of their type. The idea is that peer-group dynamics can have the same force for citizens and scoundrels, though working in the opposite direction.

Crime

Crime in this model is represented in the model by a tile covering one a square. An initial number of crimes is set when the model starts, and scoundrels make more as the model steps progress. In order to determine what the relevant range of crime rate was, an analysis of the actual crime rates of American cities was undertaken. The model is thus focused on crime rates between 1 and 25 percent, as this tends to be the range present in most major U.S. cities [Bureau of Justice Statistics].

Initial Experiments and Preliminary Results

Sensitivity Analysis

After construction of the model, the first task undertaken was a sensitivity analysis, focusing on parameters that seemed to drive the crime rates toward either unbelievably high or low. A parameter sweep was undertaken to determine which of the parameters contributed most to changes in crime rate. Because many of the parameters interact with each other, many different combinations were attempted. From this it was determined that the greatest determinant in crime rate wasn't actually any one of the parameters on their own, but the difference between the dissipation/empty effects that had the greatest impact on crime rates over all. The analysis determined that a statistically significant (at the .001 level) correlation exists between the difference of the "ciitzen's empty effect" and that of the scoundrel. For the run involving many of the parameters swept, this correlation explained over 50% of the variance in the crime rate (r-squared = .5087). Any difference greater than .004 drives the model to astronomical or nonexistent crime rates. That is, the model is very sensitive to the parameter differences between the dissipation of a citizen's desire and the accumulation of a scoundrel's confidence in an environment with empty streets. This matches with some of the theoretical base of the Routine Activity Theory of crime [Cohen & Felson 1979], which indicates that a criminal's propensity to commit crime is dependent partially on their perception of the likelihood of getting away with it. If the streets are empty, the criminal is likely to gain confidence very quickly and engage in crime. Conversely, while not couched in a specific theory of crime, if a citizen sees no one else around for an extended period, it seems likely that they may be less likely to feel committed to the neighborhood. Obviously in the real world there are many confounding variables, but the model seems to do a interesting job of pointing out the importance of this difference. In analysis, the fact that this variable is so sensitive is not surprising. A simple look at the model indicates why: with 55 agents on a grid of 2500, most of their time will be spent not encountering other agents, in empty space.

Temporal variance

One of the goals of the model was to attempt to reproduce the temporal variance that crime in large cities tends to have. After the sensitivity analysis identified the scope of some of the key parameters that would keep the crime rate from settling in an extreme, the crime rate was necessarily variable. The fact that there are costs associated with crime and cleaning up of crime that makes a criminal and citizen likely to engage in it again right after they have done so, coupled with the fact that their desires and activation points are randomly determined according to a random distribution ensures that the rate will fluctuate as different criminals and citizens act according to where on the random distribution they are.

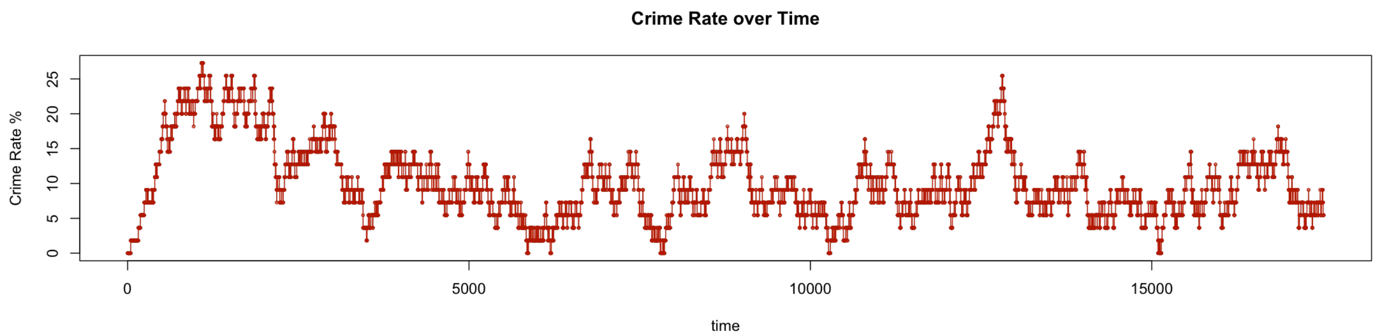


Figure 1. Crime Rate varies over time

Another interesting feature of the fluctuating crime rate through time is the affect that the bravado a moment before has on it. A rough cycle is formed by the push of crime and lying low coupled with the push to clean it up. This can be seen here:

The black detail box in the combined graphs to the right show what a relatively small change in the aggregate citizens' desire to act on the environment (the gray line) can create a much larger swing in the crime rate (the blue line). The red line is the widely fluctuating scoundrel bravado (there are only a small number of scoundrels, any change in one has a large impact on aggregate).

For the aggregate citizen bravado drop of approximately 4%, the crime rate percentage jumped from around 7 to around 30. This is largely due to seemingly random fluctuations in the citizens' movements around the grid and the costs (to them) of cleaning up the last spike in crime.

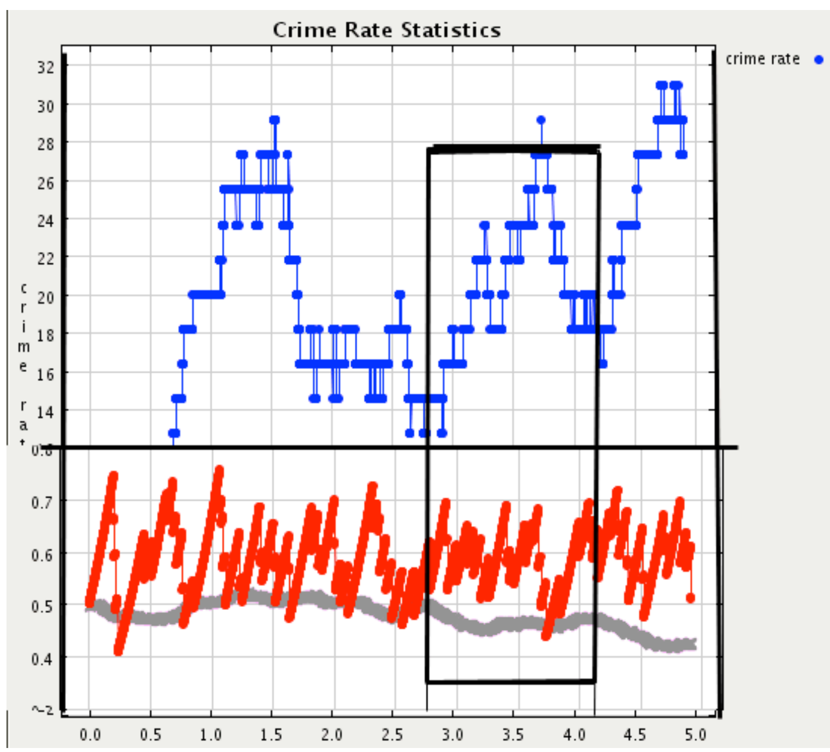
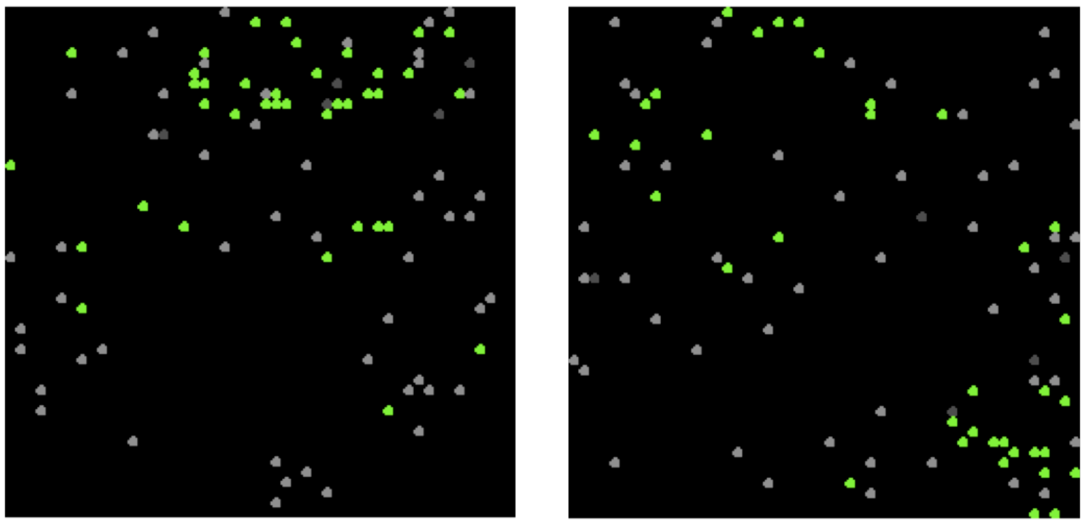


Figure 2. Dependent cycles in Crime Rate (blue) and Bravado Rates (red, gray)

Spatial Variance
Besides Temporal Variance, this paper also aimed to explore the spatial variance in crime rates. One of the popular theories of crime is the so-called "broken windows theory" [Wilson & Kelling, 1982], which alludes to the idea that crime is its own attractor: crime leads to more crime. In this model, if a criminal spots crime, their confidence gets a boost, and they are more likely to commit crime themselves. As suspected, this did indeed lead to increased clumping. A qualitative analysis shows this occurring with even for low values for the crime multiplier (around .05 or 5%).



Figures 3 & 4: Clumping of Crime at low Crime Multiplier (5%)

Quantitatively, this effect becomes even more pronounced for larger crime multipliers and a definite trend becomes apparent when the Standard Deviation of the X coordinates of the crime placed in the environment are plotted against strength of the crime viewing's affect on the criminals propensity to commit crime.

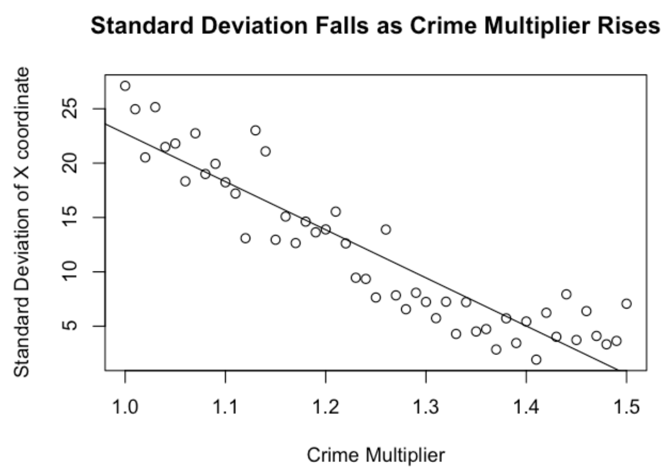
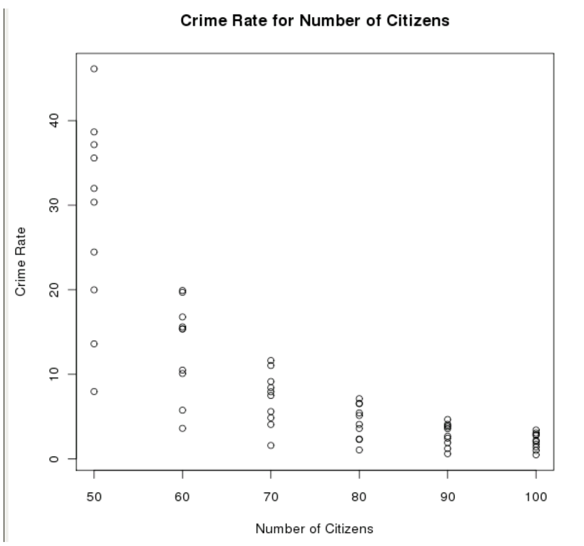


Figure 5. Broken Windows Effect: the Crime Multiplier's effect on the Standard Deviation of Average Location (x)

Notably this plot seems to be asymptotic near 0, but the line mapped shows it as linear: the linear relationship was statistically significant and a reasonable estimation for our purposes.

Density & Population

Another potentially interesting effect that the model demonstrates is that with increasing number of citizens, both the crime rate and standard deviation in the crime rate drop precipitously. This is counter-intuitive, as one would imagine that as population rises, so would crime. However, because the scoundrel percentage is being held at approximately 10% of the population, and the additional scoundrel do not overwhelm the effects of citizens being in more contact with the additional citizens. Anecdotally, it is commonly known that NYC has a far smaller crime rate than their population would entail. This may be for similar reasons: New York City's population density is twice that of the next most densely populated city in America. All those additional people may, like the model, be providing additional eyes with which to look out for crime.



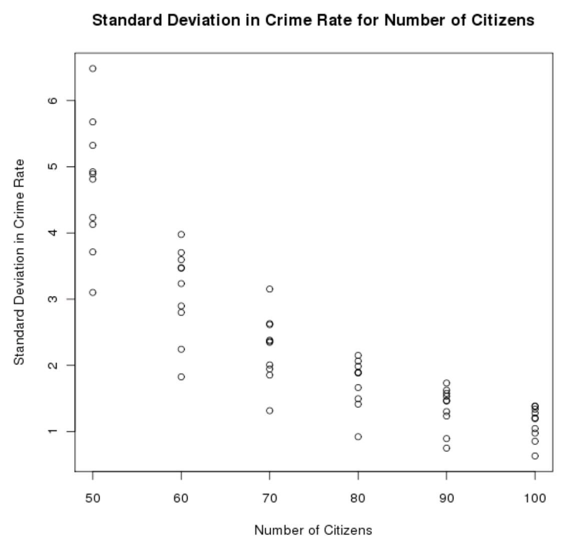


Figure 6 & 7, Crime Rate and Standard Deviation of Crime Rate for Number of Citizens

In Group Activation Pressure

This model also aimed to test the power social influence of those not just likeminded in the community, but actively engaged with it as well. While a full analysis of the effects have not yet been determined, it is clear that the activation multiplier does have a statistically significant (alpha = .001) effect on the crime rate, where communities with higher overall involvement have lower crime rates. This is not surprising, but it is interesting: the involvement bonus worked equally on both groups, but in opposite directions; the scoundrels were getting as much of a bonus in the "highly activated" community as the citizens. However, because they are only 10% of the population, their grouping pressure is not as frequently applied, thus there activation level stays the same, and is held lower in comparison to the activation level of the citizens.

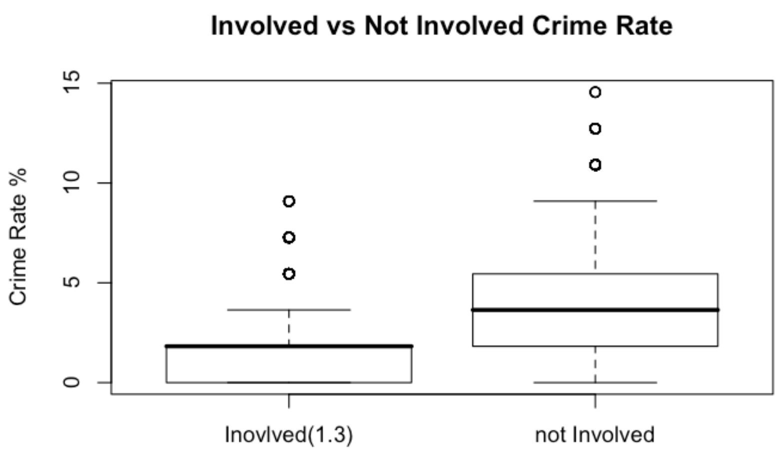


Figure 8. Crime Rate difference between communities with involvement bonus vs. those without involvement bonus

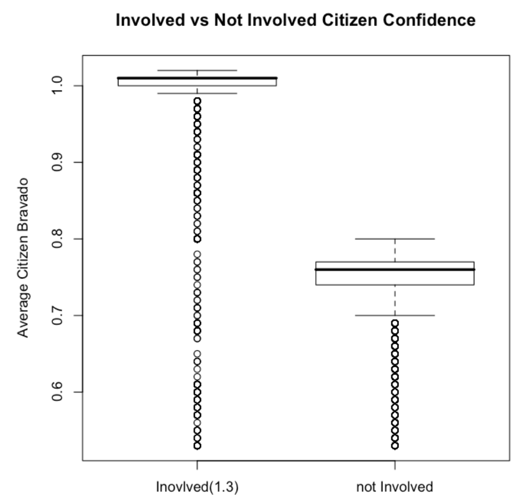


Figure 9. Citizen's activation Level difference between involvement bonus and not communities. The "involvement bonus" community's activation level is such that most of the population is always engaged.

Discussion & Future Work

This paper and model together form a rough attempt to build a platform for the analysis of crime rates and variance among American cities using an Agent Based Model. As such, it provides interesting, though not ground breaking analysis of some theoretical factors in criminology.

Many questions remain with regard to the parameters: How much would a person's motivation to fight crime change in response to persistent crime in their neighborhood? The current model depicts citizens that experience fatigue as they continue to fight crime, but there is at least one type of individual who apparently does not have this behavior: police officers. Additionally, how much crime and criminals do fellow criminals need to witness before they feel confident that they too should commit crimes? These are not questions that are easily empirically resolvable. This is an opportunity for agent-based models in general, and this one specifically: the ability to set nearly all of the parameters allows a great deal of flexibility in experiments that could be conceived of and tested. For example, an initial sweep of some variables returned only modest affects on the crime rate (probability of random move, number of initial crimes,) but may have considerably more impact when paired with other affects. This flexibility comes at the cost of some complexity in analysis: because some of the parameters interact with each other, any change in one has the possibility of disrupting the balance of the model and drive the crime rate to extreme values, unheard of values.

To dock this with real data provides both an opportunity for considerably richer, more thoughtful analysis, but it will also require a much more thorough understanding of the parameter interactions.

Finally, the model could also usefully be extended to translate the two discrete groups into continuous distribution(s) of agents with different predilections toward crime. This future direction would better reflect that the two groups, citizens and scoundrels are an oversimplification, and considers an agent's propensity toward crime on a continuous scale, from those who value the rule of law heavily enough to enforce it, through those who have no particular distaste or predilection, to those at the other end of the spectrum to those who are openly antagonistic to the rule of law, career criminals.

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Data about crime rates and population retrieved from The United States Bureau of Justice Statistics and The Census

Appendix A: Link to Model
Please see http://cscs.umich.edu/~rlr/CSCS530/Main/Jeremy

Appendix B: Model Parameters

numCitizens - number of citizens

numCrimes - number of initial crimes

numScoundrels – number of individual predisposed toward crime

citizenBravadoSD – the standard deviation of the bravado scores

iniScoundrelBravadoMean – the mean of the distribution of bravado scores

probRandMoveMean – the mean of the distribution of the random move probabilities

probRandMoveSD – the standard deviation of the distribution of the random move probabilities

sizeX – the width of the world

sizeY- the height of the world

useTorus – whether or not the world uses a torus

crimeMulti – the crime multiplier: how much seeing crime affects a criminals propensity to commit crime

emptyMulti – the emptiness multiplier: how much being alone affects a criminals propensity to commit crime

bravadodrop – the drop in bravado a scoundrel experiences after committing a crime

scnBravadoActionLimit – the minimum bravado necessary to commit a crime