*Euro. Jnl of Applied Mathematics* (2010), *vol.* 21, *pp.* 275–281. © Cambridge University Press 2010
doi:10.1017/S0956792510000070 

# What every mathematician should know about modelling crime

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(*Received 3 September 2009; revised 8 February 2010; accepted 9 February 2010; first published online 21 April 2010*)

This paper by a criminologist explains why it makes more sense to model criminal acts than to model criminals, how many preconceptions about crime can mislead modellers and offers some simple crime modelling ideas. Many opportunities for simulation now exist, and new opportunities for real-data modelling are emerging. The author suggests mathematical models of crime, including offender foraging for crime targets, as a rich area for future research.

## 1 Introduction

Crime confuses people for many reasons. New media seeking sensation offer examples of crime that are far from representative. Public preconceptions of crime and criminals are spurred on by emotions and misinformation. Many social science disciplines try their hand at crime without really learning much about it. Legal complexities undermine clarity about what is a crime and what is not. Perhaps most importantly, criminology is a pre-paradigmatic field that itself conveys more confusion than clarity. It is rich in ideas and descriptive knowledge, but does not always provide mathematicians the guidance they might need to produce mathematical models.

Moreover, crime data pose a special challenge for modellers. Police do not make all their data available to scholars, and what they have contains many systematic errors. Many crimes are under-reported by citizens to police and by local police to higher level entities. Unreported crimes far exceed those reported. Moreover, reporting rates vary substantially by crime types. Auto theft is often over-reported due to insurance fraud. Specific acts of illicit drug intake are especially underreported in official statistics. Most importantly, much crime is committed by people we do not normally consider to be offenders. Minor crime far exceeds major crime, yet often data on it is subject to the least quality control. The mathematical whiz cannot depend on individual or local data measuring accurately what happens from hour to hour and day to day. On the other hand, data on the overall picture has led to an accumulation of detailed knowledge about criminal acts in their diversity, including where and when they occur and how they are perpetrated. Such data are improving as we speak, and possibilities are opening. Still, the mathematical modeller who works closely with the tangible features of crime will do better than the one who looks for deep meaning in crime data. Mathematicians should also be aware that their most advanced models are unlikely to solve basic issues about crime. I submit that the main contribution of mathematics is clear definition and clear thinking. Indeed, mathematical *discipline* and *systematic thinking* may prove much more important than mathematical fanciness in helping us learn more about crime.

To understand crime and model it, mathematicians should be aware of five basic fallacies (see Felson, 2003): (1) The *dramatic fallacy* means emphasising well-publicized crimes, such as homicide, while forgetting that ordinary thefts, small fights and minor drug abuse dominate the world of criminal activity. (2) The *not-me fallacy* consists of believing that offenders are drawn from a different population than you. In fact, most of the population has committed criminal acts at some time and the interplay of legal and illegal activity is significant. (3) The *ingenuity fallacy* means overrating the skill required to commit a crime. Most criminal acts are simple to do, even though the victim hates to think that they were so easily defeated. (4) *The cops-and-courts fallacy* means overstating the role of police and the others in the justice system. In fact, most crime occurs without police being informed; even when police are informed, limited amounts of information may enter the public record. Finally, (5) the *agenda fallacy* is to link crime reduction to your favourite religion, ideology or political agenda. The right blames crime on the left and the left blames crime on the right. Crime in fact has little to do with ideas or politics. It is a practical matter, and should be modelled accordingly.

## 2 Fundamentals

The fundamentals of crime are found in the routine activity theory. Start with three elements: A likely *offender* must find a suitable *target* without a capable *guardian* to prevent the crime. The most likely target is something easy to steal or to overcome. The most capable guardian is an ordinary citizen whose presence or proximity serves to discourage crime. It is easy for a mathematician to conceptualise these three elements as they move about in space and time. Any setting with many likely offenders and suitable targets and few capable guardians will therefore be exposed to substantial crime risk. With these elements absent, crime risk goes down. Eck (2003) has extended this simple model by adding some other elements to produce the 'crime triangle' The offender gets away from personal handlers to find places without a place manager, then targets without guardians. The crime triangle adds many new ideas for geographic thinking and mathematical modelling. Fortunately, some agent-based mathematical models and simulation models linking crime and routine activities are now entering the literature. Excellent sources include

- A major research and modelling endeavour organized by Patricia and Paul Brantingham at Simon Fraser University's ICURS Lab (see http://www.sfu.ca/icurs);
- A volume edited by Liu & Eck (2008) at the University of Cincinnati;
- Papers by Elizabeth Groff at Temple University (2007a, 2007b);
- Work by Kate J. Bowers and Shane D. Johnson at University College London (see http://www.jdi.ucl.ac.uk/people/academic/bowers.php);

- A UCLA based consortium organized by Jeff Brantingham (see http://paleo.sscnet.ucla.edu/ucmasc.htm; Brantingham & Tita (2008); and
- Geographic profiling work organized by Rossmo (1999).

In addition, important new mathematical modelling efforts are beginning at the University of Chile under the direction of Professor Raúl Manásevich.

Modellers should remember that the greatest crime variation occurs from hour to hour. The reason for this is that crime opportunity is fleeting. Indeed, those who speak about 'bad neighbourhoods' might not know much about crime. The fact is that crime varies greatly within high-crime neighbourhoods. It can be very high on one block or one corner, or even a half block, while relatively low or moderate in the rest of the 'high-crime' neighbourhood. Crime can be high at dusk or after dark but rather low at other times. Crime can be high just after school but low the rest of the day and even on weekends. Crime is a very local matter in time and space (although an exception is presented later in this paper, showing how crime's impact can widen and come to dominate a larger urban area.) That gives many openings for mathematical modelling, but only if they understand crime's reality.

The opportunity to carry out a crime is central for its reality (Felson & Clarke, 1998; Clarke & Eck, 2005). That opportunity is also essential for mathematical models of crime. Such models fare better when linked to the tangible world, and opportunity theories provide that link in clear language that can be translated into mathematical presentations.

## 3 Foraging offenders

Many offenders do not forage at all, but instead lie in wait for their victims to go to bars or entertainment spots or to go home after work or school. Other offenders encounter victims quite by accident. But some offenders forage for their victims in much the way that animal predators forage for prey. It is quite remarkable that the foraging principles found in animal ecology apply quite well in the field of crime[1].

Three generalities can help mathematical modellers understand crime foraging (Felson, 2006):

(1) *Offenders are relative generalists*. It is usually impractical to commit just one type of crime always. It is also impractical to commit all types of crime. That's why active offenders tend to commit a variety of crimes, without doing everything.

(2) *Offenders are moderately regular*. If offenders were totally random, they would find fewer targets and meet less success. But if they were totally regular, they would be more likely to be caught and less likely to find new targets.

(3) *Younger offenders act in groups*. As offenders age they are more likely to forage alone and commit crimes alone.

Mathematical modellers should note that offenders have regularities, but are not mechanical. Thus the *life sciences* assist us more than the physical sciences in helping us model

[1] See Brantinghams, 1991, pages 1–55; Rossmo, 1995; Felson, 2006; Bernasco, 2009; Johnson, Summers and Pease, 2009.

crime. Offenders are living beings, responding to cues, learning and not always acting the same as one another or the same each time.

## 4 Crime opportunity as the central concept

The opportunity to carry out a crime is the central concept to assist mathematical modellers. Such opportunity has been explained in Felson & Clarke (1998) as well as Clarke & Eck (2005), and is highly akin to scientific approaches to studying plant and animal ecology (Felson, 2006). Below I offer two simple mathematical models as examples of how crime grows or declines, rather like other living processes nurtured by their environments. Crime opportunity is a form of environmental nurturing. As mathematicians learn more about crime opportunity, they will see many more chances to apply mathematical models to understanding it. Perhaps this process will stimulate the mathematical imagination.

## 5 Model 1 – how burglary multiplies into other crimes

Crime opportunity is generated in large part by the routine legal activities of everyday life. Above we discussed how everyday life allows likely offenders to find suitable crime circumstances. But we also need to consider how one crime sets the stage for another crime, that is, how one crime enhances the opportunity for other crimes to occur.

Accordingly, we may divide a criminal incident into three parts: (1) its prelude, (2) the incident itself and (3) its aftermath. Moreover, criminal acts are often sequential, such that the aftermath of one crime incident is the prelude to the next incident. For example, the aftermath of a burglary is often the prelude to selling stolen goods, another crime. Selling stolen goods is often the prelude to another crime, buying stolen goods, which in turn is linked to re-selling those goods. Re-selling is also closely linked to the next cycle of buying and re-selling stolen goods.

Thus each burglary can set in motion a sequence of criminal events. Here is one simple sequence:

1. somebody burgles a home and takes the television away;
2. that burglar then illegally sells the television;
3. to someone who knows it is stolen; and
4. who re-sells it.

This sequence already contains four illegal acts: burglary, illegal sale of stolen goods, illegal purchase of stolen goods and another illegal sale of stolen goods. Now let us imagine a population of 1,000 burglaries, a subset of these involve only cash and another subset involve stolen goods. If about 400 of these involve property, which is then sold illegally (hence bought illegally). If 300 of these are re-sold illegally, we end up with the following:

| | |
|---|---|
| Initial burglaries | 1,000 |
| Illegal sales of stolen goods | 400 |
| Illegal purchases of stolen goods | 400 |
| Illegal re-sales of stolen goods | 300 |
| Total crimes | 2,100 |

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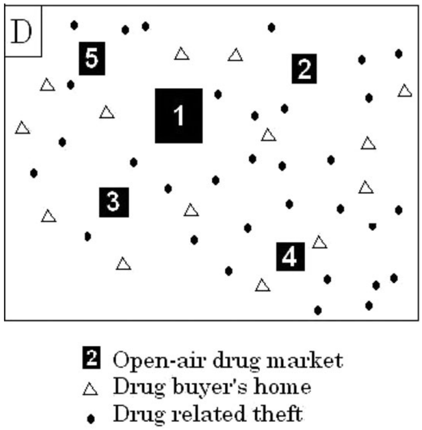


FIGURE 1. Exhibit 1 – A wide drug area. How did this happen?

The implied crime multiplier from this analysis is 2.1. Studies of offender and of victim behaviour are conversant with these findings. This calculation neglects the impact of burglaries on illegal drug purchases and sales, as well as burglary's independent contribution to public drunkenness or violent crimes involving alcohol. However, the calculation implies that every thousand burglaries generate at least twice as many other crimes. On the other hand, every thousand burglaries prevented will probably prevent at least as many other offences, with various degrees of indirectness.

## 6 Model 2 – repetitive spread of crime

Many mathematical models use fractals or other repetitive models to show how a single rule can explain a development pattern that, at least in the end, appears complex. Such thinking helps us with crime analysis, too. Exhibit 1 (Figure 1) offers a stylised map of a wide drug-dominated area in a low income part of a city. It includes five open-air drug markets, several homes of drug buyers and several drug-related thefts helping people get the money to buy drugs.

The problem is to figure out how such a drug area, with its widespread problems, could have emerged. Exhibit 2 (Figure 2) presents a speculative idea for how this might have happened. Exhibit 2A (Figure 2a) shows an initial outdoor drug market serving a few buyers and leading to a few property crimes in its relatively limited vicinity. Over time, these patrons begin to soften up the surrounding area as they spread farther in search of crime targets. Additional drug buyers enter from nearby areas, until the first drug market grows – depicted in Exhibit 2B (Figure 2b). In time, there is enough business for a second drug market to open up, as seen in Exhibit 2C (Figure 2c), with more property crimes occurring and more households involved in drug purchases. Over time, the growth in the drug area leads to D, as depicted in Exhibit 1 (Figure 1), with five outdoor drug markets, many households buying drugs, and many property crimes to support their illicit purchases. Thus a simple rule for drug purchase opportunity helps us understand the growth process and why the drug area becomes so wide. This has an important policy lesson: Do not allow drug sales to take hold of the best spot, or they will lead to a wider

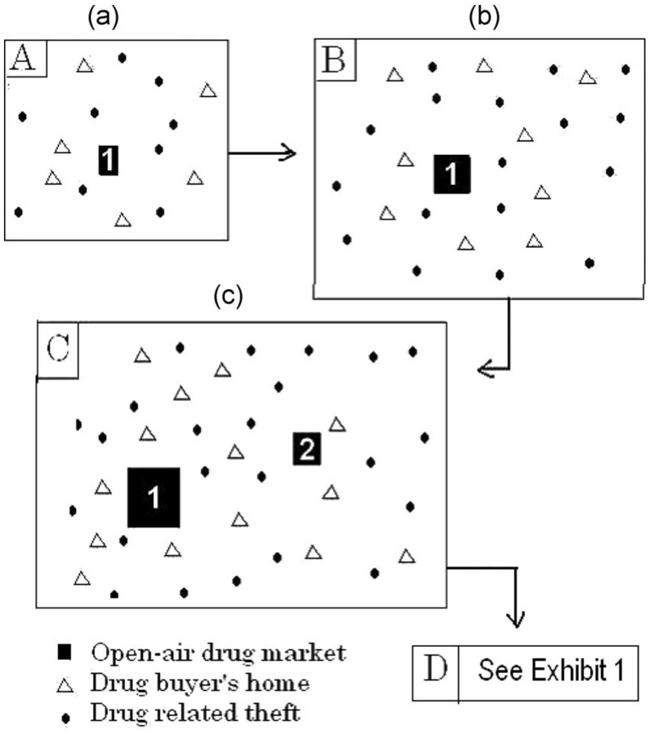


FIGURE 2. Exhibit 2 – Steps that might lead to a wide drug area.

growth of illicit drugs and related crimes[2]. Conversely, denying drug sales their best sales locations has a major impact in preventing such illicit activity from taking over in a broad sense. To model the above example, one would need detailed and sequential data on the growth of a drug market during a broad and crucial period of its development. I have no such data. But I can at least show how a community might move from one point in its history to another by relatively direct processes by which the opportunity for one crime has a generative impact on other crimes.

A future task is to model this using detailed month-by- month data on how a drug market spreads in a local area. One needs to specify a 'seed' and show how it spreads repetitively and sequentially. In any case, mathematical thinking helps discipline us as we think about this problem.

## 7 Summary

Criminology is a pre-paradigmatic field not quite ready for ordinary mathematical modelling. But it is ready for mathematical reasoning and precision, for descriptive work and for dialogue with mathematicians. It is unlikely that the latter will swoop in with detailed models to solve the basic questions. Nor is it likely that mathematicians will do better

[2] The ideas in this section are drawn almost entirely from George Rengert, perhaps the world's foremost geographer of crime (see Rengert, 2000, 2004).

than anybody else in modelling offenders as people. On the other hand, mathematics can converse quite well with those who study how crime occurs, when, where and how it can be contained in practical fashion.

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https://doi.org/10.1017/S0956792510000070 Published online by Cambridge University Press