A LIKELIHOOD-BASED APPROACH TO DEVELOPING EFFECTIVE PROACTIVE POLICE METHODS

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Proactive policing methods are crucial to ensuring safety and security in line with the UN Sustainable Development Goals. This chapter considers aoristic crime data, where an event occurs within a known time interval, but at an unknown time. We introduce a Bayesian likelihood-based approach to estimate occurrence times of property crimes given a known time interval by modelling victim and offender behaviour as stochastic processes. The model can capture non-homogeneous behaviour by both the victim and the offender and underlying factors leading to patterns in crime occurrence times. We test our model on an open-source aoristic crime data set from the USA, comparing our approach to previous approaches. The model determines the most likely occurrence times through parameter estimation methods, finding potential hot spots, and allowing police to adapt proactive policing strategies. This ties in with SDG 16, which involves strengthening institutions and working towards safe and secure societies.

Keywords:
aoristic crime data,
Bayesian statistics,
residential burglaries,
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VERJETNOSTNI PRISTOP K RAZVOJU UČINKOVITIH PROAKTIVNIH POLICIJSKIH METOD

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Proaktivne policijske metode so ključnega pomena za zagotavljanje varnosti in zaščite v skladu s cilji trajnostnega razvoja Združenih narodov. V tem poglavju obravnavamo aoristične podatke o kriminaliteti, kjer se dogodek zgodi v znanem časovnem intervalu, vendar ob neznanem času. Predstavljamo Bayesov pristop, ki temelji na verjetnosti za ocenjevanje časa pojava premoženjskih kaznivih dejanj glede na znani časovni interval z modeliranjem vedenja žrtve in storilca kot stohastičnih procesov. Model lahko zajame nehomogeno vedenje žrtve in storilca ter osnovne dejavnike, ki vodijo do vzorcev kaznivega dejanja v času dogajanja. Naš model smo testirali z aoristično analizo niza statističnih podatkov kaznivih dejanj odprtega dostopa iz ZDA in primerjali naš pristop s predhodnimi pristopi. Model določa najverjetnejše čase pojava z metodami ocenjevanja parametrov, iskanjem potencialnih žarišč in omogoča policiji, da prilagodi proaktivne policijske strategije. To je povezano s ciljem 16, ki vključuje krepitev institucij in prizadevanje za varne družbe.

1 Introduction and Sustainable Development Goals

In 2015, the United Nations established seventeen Sustainable Development Goals (SDGs). Introduced as part of its 2030 Agenda for Sustainable Development, they provide a sustainability framework for the 15 years following their announcement. Sustainability is addressed in various contexts, ranging from environmental to geopolitical sustainability. Each SDG is accompanied by a list of targets and corresponding indicators, outlining specific actions to achieve each goal. Numerous SDGs intersect with active research areas and interests in criminology. Goal 16 aims to "promote peaceful and inclusive societies for sustainable development, provide access to justice for all, and build effective, accountable, and inclusive institutions at all levels" (United Nations, n.d.).

To increase the effectiveness of government institutions, it is essential to have a deep understanding of criminal behaviour so that potential crimes can be averted before they are committed. Proactive policing methods based on theories of social and criminal behaviour are crucial in this respect. Examples of these methods include hot spot policing (Sherman & Weisburd, 1995), broken-windows policing (Wilson & Kelling, 1982), and focused deterrence (Kennedy et al., 1996), also known as pulling levers policing, among others. While the effectiveness of certain proactive policing methods is disputed (e.g., Harcourt & Ludwig (2006), relating to broken windows policing, or Gau & Brunson (2010) relating to police perception in general), they represent a broader shift from reactive to proactive policing, where the police serve as a greater community force instead of simply focusing on apprehending suspects (National Academies of Science, Engineering, and Medicine, 2018). In this way, proactive policing methods can potentially contribute to forming fairer, safer, and more robust institutions, as SDG 16 states.

The development of statistical models for crime prediction can also be viewed through the lens of proactive policing. Such approaches are often known as predictive policing methods (Perry et al., 2013) and allow for quantitative analysis of crime data. While these approaches can be powerful and have made significant contributions to successful proactive policing methods in certain cases (Santos, 2014), they are not always viable for certain types of offences (Felson & Poulsen, 2003). Rarely reported offences are often not amenable to analysis due to a lack of data, and many otherwise viable, reported offences can contain a lot of uncertainty.

An example of this is residential burglaries, as people often return home to find that their place of residence has been broken into, not knowing the actual time of occurrence. Though it may be of little consolation to the victim to know an approximate time of occurrence, it may be of great interest to the police and assist victims in preparing for future burglaries.

While these factors severely limit the effectiveness of analysing imperfect data, criminologists have developed methods to address such issues. Many criminologists noticed limitations in purely spatial analysis of crimes and sought to focus more on temporal data (Ashby & Bowers, 2013; Briz-Redón, 2023; Helms, 2008; Ratcliffe, 2002; Ratcliffe & McCullagh, 1998). To deal with temporal uncertainty, they developed a scheme by which incomplete, censored crime data could be analysed temporally. This class of crimes is known as "aoristic", a word derived from the Ancient Greek root aóristos, meaning "without defined occurrence in time". Similarly, the aorist tense, which is present in languages such as Greek, describes a singular event occurring at an indeterminate time in the past. Aoristic crime data analysis falls under the subcategory of predictive policing methods within the broader field of proactive policing methods. Knowing the most likely time of occurrence allows police to draft proactive policing strategies around the most likely occurrence times. These analyses could, therefore, assist police in implementing proactive policing methods that contribute to strengthening institutions and ensuring safe and secure communities, one of the aims of the United Nations' sixteenth SDG.

2 Review of Theories on Criminal Behaviour

In 1979, Lawrence E. Cohen and Marcus Felson published the work "Social Change and Crime Rate Trends: A Routine Activity Approach", describing the effect that routine activities have on crime patterns. Using criminological data, they argued that shifting trends in human behaviour led to an increase in the crime rate in the USA in the 1970s, which initially seemed paradoxical (Cohen & Felson, 1979). The higher crime rate was surprising, as the USA was experiencing increasing prosperity and significant social change, factors that were generally understood to lead to a decrease in crime.

This work, among others of its kind, led to a shift away from focusing on the characteristics and psychology of criminals and towards social disorganisation theory (Bursik, 1988). This theory suggests that places of residence and general spatial factors play a significant role in shaping the distribution of crime in a city, perhaps even more so than the psychology of an individual (Gaines & Miller, 2003; Shaw & McKay, 1942). Hawley's human ecological theory of community structure provides intuition in this respect, asserting that time and location dependence underlie community structure itself and are crucial in organising a community (Hawley, 1950). Social disorganisation theory has waxed and waned in popularity through the years (Kubrin & Weitzer, 2003), especially since testing the theory empirically has been difficult (Heitgerd & Bursik, 1987). Additionally, Bursik (1988) noted that many perceived flaws in social disorganisation theory might arise from the misapplication of the theory or the difficulty in measuring social disorganisation. Nevertheless, Sampson and Groves (1989) found support for the idea that "social-disorganisation theory has vitality and renewed relevance for explaining macro-level variations in crime rates". The idea that time, place, and community structure are relevant factors for criminal activity, instead of solely focusing on delinquent individuals, is well substantiated (Kubrin & Weitzer, 2003). These ideas can be considered as building blocks from which the statistical model outlined later in this chapter takes inspiration.

Taking routines into account, as well as the effects they have on crime, is often known as the routine activity approach (Cohen & Felson, 1979). For example, people living in neighbourhoods tend to build mental maps of their immediate surroundings, helping them avoid places that may be susceptible to crime (Nasar & Fisher, 1993). This leads to a concentration of crimes in certain regions of cities where crime is "easy, safe, and profitable" (Brantingham & Brantingham, 1995). Resulting from this shift in philosophy within criminology is the realisation that spatiotemporal analysis can potentially provide important insight into the field, as these methods aid in modelling neighbourhoods and community structures. Together with the ideas from the social disorganisation theory outlined in the previous paragraph, this provides a basis upon which a model can be built.

As a result of the move towards spatiotemporal analysis, research within criminology has focused on determining the most probable locations of crimes (Brantingham & Brantingham, 1995; Felson & Poulsen, 2003; Wilcox, 1973). However, research has yet to be focused on temporal interdependence to the same extent, even though the routine activity approach may also inform patterns in temporal variation (Ashby & Bowers, 2013; Cohen & Felson, 1979; Ratcliffe & McCullagh, 1998). Hawley wrote about three temporal factors of community structure: rhythm, tempo, and timing. Rhythm refers to the periodicity of event occurrences, tempo to the number of events per unit time, and timing to the coordination of activities between members in a community (Cohen & Felson, 1979; Hawley, 1950). Due to several factors, such as women's increased participation in the workforce and an abundance of cars, more activities began to take place away from places of residence starting in the 1960s and 1970s, a trend that has continued to the present day (Felson & Poulsen, 2003). As a result, there was a shift in the times of the day at which residential crimes were more likely to be committed (Cohen & Felson, 1979; Felson, 1998; Felson & Cohen, 1980), especially for crimes that are opportunistic in nature (Cohn & Rotton, 2003; Felson, 2006). Consequently, it seems implausible to assume that crimes are equally likely to occur at any given time, an assumption often made in aoristic crime modelling methods. These methods, introduced by Ratcliffe and McCullagh (1998) and extended by Ratcliffe (2002), and Ashby and Bowers (2013) allow for the estimation of occurrence times in a temporal crime dataset when only a time interval is known. This is often the case for crimes such as burglary or arson (Ratcliffe & McCullagh, 1998).

Additionally, inspired partially by Hawley's three temporal factors of community structure (Hawley, 1950), it seems plausible that crimes in each neighbourhood are influenced by each other. If the police decide to crack down on crimes at certain hours, crimes may start occurring at different times due to heightened police presence. Furthermore, in neighbourhoods where houses or apartments have similar layouts, a successful burglary may lead to an increase in crime in that neighbourhood due to the near-repeat effect (Bernasco, 2009; Short et al., 2009). Therefore, it may be erroneous to assume that burglary times and frequencies remain constant over time.

In this chapter, we introduce a model that accounts for differences in crime frequency over time, considering the behaviour of both the victim and the offender. This is possible due to the non-homogeneous nature of the model. This parametric model works with interval-censored crime data, better known as aoristic crime data, and aims to estimate the most likely occurrence time. The model is Bayesian in nature and works with likelihoods, departing from methods described in Ashby and Bowers (2013). These factors lend the quantitative analysis performed in this chapter relevance within the context of what is known in the field. This will hopefully lead to safer and more secure communities, in line with Goal 16 of the 2030 Agenda for Sustainable Development.

3 Proactive and Reactive Policing Methods

There is a key difference in philosophy between proactive policing methods, where the work presented in this chapter falls, and reactive policing methods. In the past, the police were often seen primarily as a reactive force, apprehending alleged offenders and responding to requests from citizens (Reiss, 1992). Throughout the 20th century, police departments pushed to modernise and professionalise, with an increased understanding that the police's role includes serving and protecting the community. Along with this came the idea of proactive policing, preventing crime before it even occurs (National Academies of Sciences, Engineering, and Medicine, 2018).

In this work, we will mainly focus on hot spot policing, developed in 1995 by Sherman and Weisburd in the Minneapolis Hot Spots Patrol Experiment. The idea is to concentrate on specific geographic regions where crime incidents are or have been empirically shown to be more likely than in other regions (Eck & Weisburd, 1995; Sherman & Weisburd, 1995). This strategy effectively reduces crime in the identified hot spot without spreading to adjacent areas (Sherman & Eck, 2002). While there are certain drawbacks to this strategy, chief among them being its limited lasting effectiveness and narrow use (Rosenbaum, 2006), the National Research Council (2004) summarised that there is strong evidence for the efficacy of hot spot policing.

The model outlined in the following section of this chapter works with the idea that hot spots occur not only in place but also in time, a concept supported by significant evidence. It is informed by theories such as the near-repeat effect (Bernasco, 2009; Short et al., 2009), the routine activities approach (Cohen & Felson, 1979), and other insights mentioned previously (e.g., Cohn & Rotton, 2003; Nasar & Fisher, 1993). While this is a predictive policing method, relying on the use of statistical models and data to estimate occurrences within time windows, it assumes an inherent difference in likelihood between different times of the day, drawing inspiration from hot spot-related methods. The model will now be introduced in more detail.

4 Methodology

Typically, aoristic crime data consist of a time interval in which an event occurred, with uncertainty regarding the exact event time. For example, imagine that a woman leaves her house for work at 08:00, and returns at 17:00 (see Figure 1). Upon returning, she realises that her place of residence has been burgled. She subsequently calls the police to report the crime but is unable to provide a more precise estimate of the occurrence time than the entire time interval during which she was working. This time interval is then recorded.

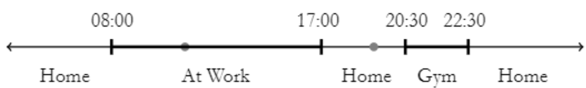

Figure 1: Example of the Schedule of a Potential Victim

Note: The bold intervals denote times when the victim is away from home.

When performing the analysis, one would like to find the most likely time the crime occurred for every time interval in each dataset. Alternatively, one might want to know the entire distribution of occurrence times. Introducing some simple mathematical notation, represent the data set by $D = \{[a1, a1 + l1], [a2, a2 + l2], ..., [an, an + ln]\}$ where a refers to the start of the time interval in which a crime occurred, and l refers to the length of this time interval. The notation $[a, b]$ represents a time interval starting at time a and ending at time b, including the endpoints. We assume that there are n crimes. Let t_i denote the estimated time of occurrence for the ith crime in the data set so that t_i is in $[ai, ai + li]$.

4.1 Methods Based on Summary Statistics

A naive approach might be to simply take the midpoint of each time interval as an estimate. For example, in Figure 1, the midpoint of the time interval (08:00, 17:00) would be 12:30. This time would then be recorded as the time of occurrence (Helms, 2008). Possible advantages of this method include that it is easy to calculate for large data sets and that for small enough intervals, the exact estimate of the time becomes less important. However, the major disadvantage of this approach is that it is entirely arbitrary. Based on what is known about property crimes, there is no good reason why this value should be chosen over others.

Similar methods, such as arbitrarily picking the start or end points of the interval, have been described (Ashby & Bowers, 2013; Ratcliffe & McCullagh, 1998). Ashby and Bowers (2013) also suggested picking a completely random point within the interval with uniform probability. These methods all suffer from the same issue as the midpoint method – arbitrary time selection. Possible interactions between occurrence times are ignored, and the assumption that all occurrence times are equally likely within a given interval is still implicitly present when occurrence times are selected in this manner.

4.2 Statistical Approaches

Some more advanced methods have been developed to perform data analysis on aoristic crime data sets. Consider a weight function over t (Ratcliffe, 2002; Ratcliffe & McCullagh, 1998). Here, for a given value of t over the union of the data set D.

$$W(t) = \frac{1}{n}\sum_{i=1}^{n}\frac{1\{a_i \leq t \leq a_i + l_i\}}{l_i}$$

Note that 1 is the indicator function, meaning that 1 is returned if t is contained in the interval $[a_i, a_i + l_i]$ and 0 otherwise. Using this method, a length-weighted sum is returned for a given point in time. This denotes the likelihood of a crime occurring at time t. To make this clearer, consider the following example where $D = \{[0.1, 0.5], [0.2, 0.4], [0.3, 0.6]\}$. The union of this set is $[0.1, 0.6]$. Evaluating W at $t = 0.2$ results in

$$W(0.2) = \frac{1}{3}\left[\frac{1}{0.4} + \frac{1}{0.2} + \frac{0}{0.3}\right] = 2.5$$

The weight function $W(t)$ can be evaluated for discretely many values of t in the observation window. In practice, one would generate many potential values of t, evenly spaced out across the observation window, and apply this function. As this is a probability mass function, one can sample from this distribution, picking random points based on how likely it is that points follow this pattern. Figure 2 shows the value of this function with the intervals overlain. One can see that the value of *W(t)* is highest in the intersection of the three intervals. While this method does add some complexity and considers multiple time intervals at once, occurrence times within a certain interval are biased towards time ranges within which multiple intervals intersect. It may be erroneous to assume that criminal activity always clusters in this way.

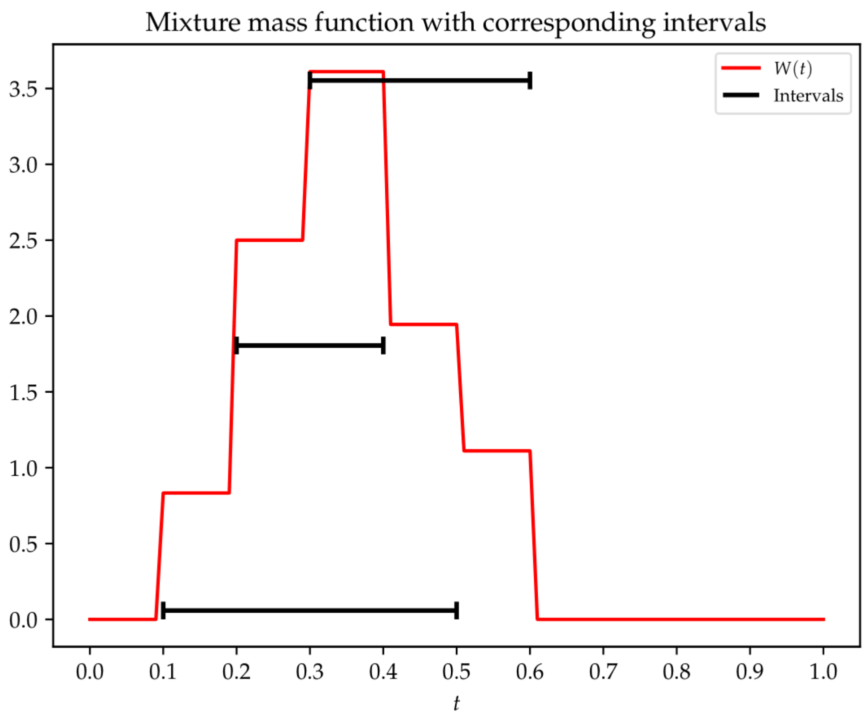

Figure 2: Example $D = \{[0.1, 0.5], [0.2, 0.4], [0.3, 0.6]\}$ Plotted Together with the Values of *W(t)* for t Between 0 and 1

4.3 Bayesian Approach

While the methods outlined earlier can have relative success in certain cases, they fail to model interaction in the data, which inherently affects the timing of events. For example, people are less likely to be home during work hours, meaning that a criminal would encounter less resistance when trying to break in at this time. Such behaviour patterns create a dynamic environment in which criminals operate. It would be advantageous to implement an interaction model, which could result in a more accurate estimation of break-in times. A model well-suited to handle this type of data is a likelihood-based model, which utilises methods from point process theory and Bayesian statistics to model interval-censored data (van Lieshout & Markwitz, 2023), making it suitable for aoristic crime analysis as well. The main advantage of this specific model is that potential occurrence times are not considered as separate data points but are part of an underlying distribution that partially overlaps with the intervals within which they range. This approach allows for more complex behaviours to be included in the model.

To facilitate such analyses, the model considers two processes: the burglar process, which contains the occurrence times, and the victim process, which contains the time intervals within which crimes occurred. In the burglar process, the model considers that occurrence times may exhibit clustering, regular, or random behaviour. The model estimates the likelihood of each of these scenarios. Clustered behaviour refers to occurrence times being close to each other, whereas regular behaviour refers to points being spread out across the observation window. Random behaviour refers to no discernible pattern in occurrence times. In the victim process, parameters are estimated regarding the length and starting point of the intervals in the data set. This allows the model to generate test data sets using these parameters, on which likelihood calculations can be performed. The model also allows for intervals of length zero, which models cases where the exact time of occurrence is known. This might correspond to situations where a security camera captures footage of a burglar breaking in, or when someone is home when the crime is committed. The two processes are later combined, and a Monte Carlo algorithm subsequently determines the most likely location of the points within their respective intervals (Meyn & Tweedie, 2009; Møller & Waagepetersen, 2004).

However, this model does come with some drawbacks. Potential interactions between points may lead to certain regions in the intersection of intervals being less favoured by the Monte Carlo algorithm during estimation (van Lieshout & Markwitz, 2023). More pressingly, absent this behaviour, it is inherently assumed that events are equally likely to occur in time. In other words, the underlying probability of occurrence remains the same across the observation window, without accounting for factors such as night or time of year. This may be a serious drawback since routine activities theory (Cohen & Felson, 1979) suggests that this is very likely not the case.

Table 1: Qualitative Analysis of Aoristic Crime Analysis Methods Discussed in the Text

Method	Non-arbitrary selection	Interaction modelled	Accounts f or time
Midpoint	No	No	No
Start/End	No	No	No
Random selection	No	No	No
Weight function	Yes	Partially	No
Initial Bayesian model	Yes	Yes	No
Updated Bayesian model	Yes	Yes	Yes

Since then, a new Bayesian model has been developed (van Lieshout & Markwitz, 2024). In the initial Bayesian model, it is assumed that the duration of time that victims are away from their places of residence follows a distribution that is entirely independent of the time of day. It is also assumed that victims have an equal probability of leaving their places of residence at all times of the day, which may not be the case based on routine activities theory. In the burglar process, it is assumed that burglars are equally likely to strike at all times of the day. All these assumptions allow for easier estimation of model parameters but make the model less capable of modelling the criminological situation, leading to the results being of questionable validity when performing analysis on real-life datasets. Since the updated model can take these factors into account, the underlying behaviour can be modelled more accurately. See Table 1 for a qualitative overview of the methods discussed in this section and their benefits and drawbacks.

The statistical theory behind the updated model is very similar to the previous Bayesian model. Regarding the burglar process, we assume that occurrence times follow some sort of initial distribution, based on either clustered, regular, or random behaviour within the recorded time range. However, it is not assumed that burglars are equally likely to break in at all times of the day. By allowing this probability to vary over the observation window (see parameter(s) β in Table 2), the modelling of "peak" or "down" times is facilitated. A function describes the distribution of these points, with the values of parameters deciding which of the three behaviours manifest themselves. We solve the inverse problem - given a data set, which parameter values are most likely?

The same approach is taken in the victim process. We assume that the intervals are generated by two distributions - one for the starting point and another for the length of the interval. However, in the updated Bayesian model, these distributions are time-dependent (see parameter(s) a and δ in Table 2). This results in the generation of more accurate test data sets, which play a crucial role in likelihood calculations. Given the data set, we then use a maximum likelihood approach to find the most likely combination of occurrence times within their respective intervals. Alternatively, summary statistics such as the mean time of occurrence or even the entire distribution of possible burglary times across all intervals can be calculated by using the same Monte Carlo methods mentioned previously (van Lieshout & Markwitz, 2024).

Table 2: Description of Parameters in the Model

Parameters	Description	Typical ranges/Examples
a	Denotes the scale of the length of intervals. If all intervals are relatively long, the estimated value of a will be higher.	$0 < a < 3$
K	Denotes the shape of the length distribution. If there are very few long intervals and very many short ones, the value of k will be lower, and vice versa.	$0 < k < 2$
δ_i, A_i, J*	Splits the observation window into J separate time ranges, A_1, …, A_J. The parameter δ_i denotes the likelihood of an interval starting in the time range A_i.	$J = 2$, $A_1 = [0, 0.4]$, $A_2 = [0.4, 1]$. $\delta_1 = 0.5$, $\delta_2 = 0.3$.
β_i, B_i, K*	In the burglar process, β_i denotes the likelihood of a crime occurring in the range B_i where B_1, …, B_K are K separate time ranges. In most cases, β_i will be close to the number of actual burglaries in the range B_i.	$K = 2$, $B_1 = [0, 0.2]$, $B_2 = [0.2, 1]$. $\beta_1 = 20$, $\beta_2 = 5$.
γ	In the burglar process, γ determines which kind of behaviour, clustered, regular or random, is exhibited. $\gamma < 1$ denotes regular, $\gamma = 1$ random, and $\gamma > 1$ clustered behaviour.	$\gamma = 1.5$ would imply crimes occurring close to each other in time.

Note: The number of ranges J and K, along with the corresponding ranges A_i and B_i are determined beforehand by visual inspection, and not estimated.

4.4 Data and Correctness

To ensure that the parameter estimation mentioned in the previous section is performed correctly, simulated data conforming to known parameter values is generated. This data is then fed back into the model to verify that the estimated parameter values correspond to the known parameter values. This process ensures that when the actual crime data is analysed, the estimated parameters take on plausible values. This is crucial, as these values are subsequently used to simulate the most likely occurrence times of crimes within the corresponding intervals.

To facilitate comparison, a standard crime data set was used for model fitting. We chose the Washington D.C. burglaries dataset (Open Data DC, n.d.) because it includes precise start and end times for burglaries within a small enough spatial area and provides enough data points to facilitate comparison (though this is still not optimal, see discussion for details). The dataset, named “Crime Incidents in 2016”, records all reported crimes within the city limits of Washington D.C. in that year, containing 37,189 records, with 2,121 of them being burglaries. The model was applied to a subset of this dataset, specifically focusing on burglaries where the end times fell in February. Only burglaries with defined start and end dates were selected, and other crimes have been filtered out for this analysis. The model’s application was restricted to a subset of the data due to computational constraints. While the frequency of crimes likely varies by time of day and season, the model can account for this in both the victim and burglar processes by choosing time ranges Ai and Bi respectively (see Table 2 for more details).

The updated Bayesian model is run on the data. Upon visual inspection of the data, it appears that fewer victims report crimes in the last few days of the month. Based on this observation, the time range A_1 is set to $[-0.2, 0.9]$, and $A_2 = [0.9, 1]$ (see Table 2 for interpretations). In these sets, the value 0 refers to midnight on the 1st of February, and the value 1 represents midnight on the 1st of March. Choosing a negative value in $A1$ ensures that crimes occurring before the 1st of February but ending within the month are also included. Therefore, the values of δ_1 and δ_2, corresponding to these time ranges, need to be estimated. We set $K = 1$, indicating that only one β needs to be calculated.

5 Results and Discussion

Figure 3 shows the time intervals and corresponding estimated occurrence times for the last week of February. As there were 120 reported burglaries in February 2016, plotting the entire month would lead to a less visually appealing graphic. See Table 3 for the exact occurrence times estimated by the model.

Table 3: Start Times, End Times and Estimated Times of the Burglaries in the Washington D.C. Dataset, Which Have Non-zero Interval Lengths

Start time	End time	Estimated time
2016-02-24 12:33:42	2016-02-24 14:57:56	2016-02-24 14:20:31
2016-02-24 19:19:06	2016-02-24 19:50:11	2016-02-24 19:29:24
2016-02-28 21:57:38	2016-02-29 02:58:04	2016-02-28 23:47:12
2016-02-28 22:57:47	2016-02-29 11:58:53	2016-02-29 04:09:10
2016-02-24 15:18:58	2016-02-24 21:49:32	2016-02-24 20:52:49
2016-02-25 10:51:39	2016-02-25 12:30:48	2016-02-25 11:16:54
2016-02-29 13:59:05	2016-02-29 21:52:47	2016-02-29 17:39:41
2016-02-25 16:51:11	2016-02-25 20:40:31	2016-02-25 18:35:16
2016-02-25 13:20:44	2016-02-25 23:26:38	2016-02-25 22:05:17
2016-02-25 17:36:05	2016-02-26 00:21:40	2016-02-25 22:09:38
2016-02-26 05:02:09	2016-02-26 06:37:17	2016-02-26 05:19:53
2016-02-26 13:52:58	2016-02-26 16:08:10	2016-02-26 15:23:10
2016-02-26 08:41:32	2016-02-26 19:30:27	2016-02-26 11:45:55
2016-02-26 13:23:02	2016-02-26 21:13:43	2016-02-26 20:12:42
2016-02-27 01:28:44	2016-02-27 02:53:50	2016-02-27 02:45:38
2016-02-26 14:53:04	2016-02-27 03:09:08	2016-02-26 18:57:18
2016-02-27 21:38:32	2016-02-27 23:54:42	2016-02-27 21:39:30

The model estimated the following parameters: $\delta_1 = 0.8$, $\delta_2 = 0.5$, $\beta = 115.06$ and $\gamma \approx 0$. The fact that δ_1 does not equal δ_2 shows that there does seem to be an inherent difference in the likelihood of crime occurrence in the last few days of February. The parameter β can be seen to be approximately equal to the number of crimes that one would expect in this configuration. As γ is much smaller than 1, this implies that crimes do not seem to cluster and instead occur further apart from each other in time. A possible explanation for this could be that there were "only" 120 crimes in 28 days, meaning that certain intervals may not overlap. For non-overlapping crimes, no assumptions can be made regarding other crimes, leading to less information being fed to the model. While the estimation procedure for γ can still be carried out, as less information is available, the exact value may be somewhat imprecise. One might expect greater clustering since it is known empirically that crimes do not occur at an equal rate across time. However, it may be the case that the spaced-out nature of the estimated occurrence times is the model considering the inherent periodicity of the data. As more likely times are followed by less likely times in roughly equal measure, points may be clustered in more likely regions but are spread out across the entire data set due to this phenomenon.

The parameters α and k take the values 2.2 and 0.3 respectively, indicating intervals are relatively long compared to the length scale, but that there are comparatively more "short" intervals than "long" intervals. In other words, people tended to be away for a relatively long time, but there were very few instances where people were away from their properties for significantly longer periods compared to other victims. Though this can be determined in different ways, such as visual inspection or gathering summary statistics, it shows that the model accounts for this behaviour during estimation.

The original burglary dataset is aoristic, meaning that only time intervals are provided. While potential hot spots can be detected using approaches such as the mixture mass function (Ratcliffe, 2002; Ratcliffe & McCullagh, 1998; also see Figure 2), this method ignores other factors that are almost undoubtedly present for residential burglaries and bias potential occurrence times towards intersections of time intervals. It has been shown that hot spot policing, and proactive policing methods in general, can effectively reduce crime (Sherman & Eck, 2002). By examining the most likely occurrence times generated by the updated Bayesian model, potential hidden hot spots in time can be detected, leading to the implementation of proactive policing methods based on this model. Detecting hot spots that are obscured by the censured or aoristic nature of the data allows for more efficient policing by implementing effective strategies during times when crime is more likely to occur. Additionally, the non-homogeneous parametrisation method for time intervals used in the estimation process allows for the generation of more accurate test datasets. This may assist both future researchers who wish to implement different occurrence time estimation methods to validate their models, and police departments wanting to perform data analysis. Data-driven analysis of aoristic crime data, along with the actions taken based on relevant findings, has the potential to make our communities safer and more secure. To achieve SDG 16, the focus must be on developing efficient and effective policing methods.

The model introduced in this chapter rectifies many issues present in estimating occurrence times for aoristic crime data, but some shortcomings should also be mentioned. Firstly, no spatial information is considered, which undoubtedly limits the effectiveness of the model. A more powerful model might make use of spatial covariates to inform crime rates at specific locations, since it is known that location affects crime rate (Brantingham & Brantingham, 1995; Sherman & Weisburd, 1995).

Secondly, this model assumes that the burglar and victim processes are independent. Relaxing this assumption would lead to greater difficulty in applying a model of this type, but it may also be more accurate in describing the actual behaviour of criminals and victims.

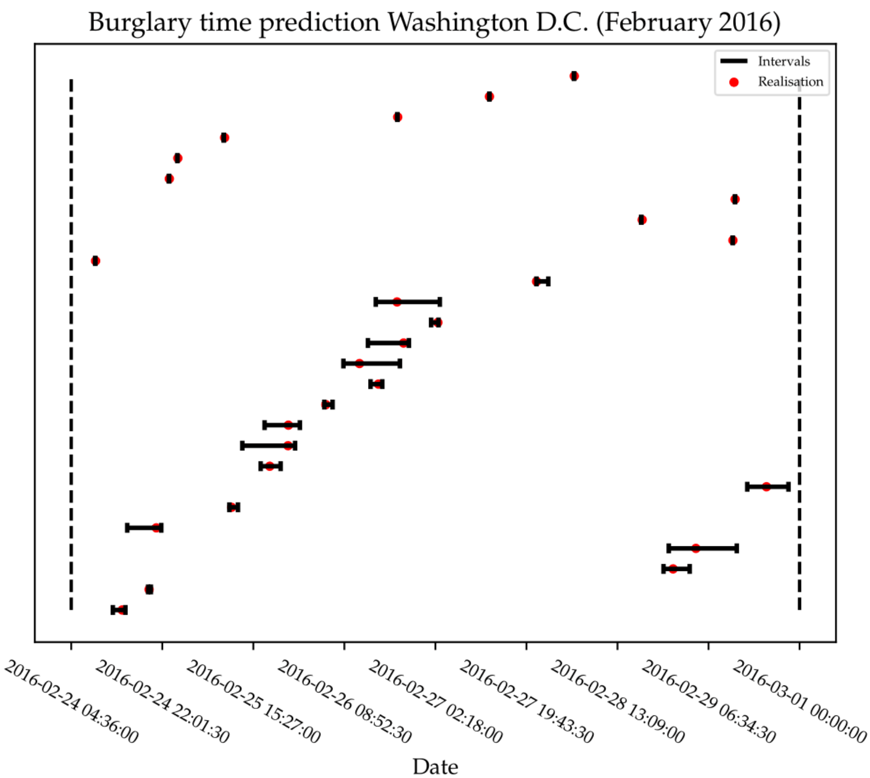

Figure 3: Simulation of the Occurrence Time of Crimes from the Washington D.C. Aoristic Crime Dataset

Note: Estimated burglary times are marked by a red point, the intervals in black.

6 Conclusion

The United Nations specifies 17 SDGs introduced to encourage global cooperation and sustainability worldwide. Goal 16, named “Peace, Justice, and Strong Institutions” aims to promote peace, sustainable development, and effective institutions (United Nations, n.d.). Proactive policing methods play a role in reducing crime when applied effectively (National Academies of Science, Engineering, and

Medicine, 2018; Rosenbaum, 2006), which in turn help to build strong and accountable institutions at all levels. Based on sociological and criminological theories such as routine activity theory (Cohen & Felson, 1979) and temporal factors of community structure (Brantingham & Brantingham; 1995; Hawley, 1950), proactive policing methods such as pulling levers policing (Kennedy et al., 1996) and hot spot policing (Sherman & Weisburd, 1995) have been developed to improve police effectiveness and strengthen institutions. Predictive policing methods, particularly those related to hot spot policing, have gained significant traction (National Academies of Science, Engineering, and Medicine, 2018). In this chapter, a model has been introduced to perform predictive modelling of aoristic crime data, which is data collected for specific types of crimes where the time of occurrence is not exactly known (Ratcliffe & McCullagh, 1998).

Aoristic crime data have been modelled in numerous ways over the years, with approaches ranging from easily calculable summary statistics methods to sampling from probability mass functions. We introduce a Bayesian likelihood model that models the burglar and the victim separately, does not assume that crimes are equally likely to occur at all times of the day, and takes into account that victims might be away from their places of residence for varying lengths of time depending on when they leave. The model also allows for data sets to be interconnected, as crimes taking place in the same neighbourhood are likely related. The model is applied to a data set of residential burglaries occurring in Washington, D.C., in February 2016. A table of most likely burglary times has been provided, along with a visualisation in the form of a graphic showing intervals and estimated times. Using these estimated occurrence times, potential hot spots can be identified, allowing police to adapt existing proactive policing methods accordingly. Taking such findings into account is crucial for meeting sustainability goals, such as the SDGs introduced by the United Nations in 2015.

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