CPC: CRIME, POLICING & CITIZENSHIP
INTELLIGENT POLICING AND BIG DATA
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Crime, Policing and Citizenship (CPC) – Space-Time Interactions of Dynamic Networks has been a major UK EPSRC-funded research project. It has been a multidisciplinary collaboration of geoinformatics, crime science, computer science and geography within University College London (UCL), in partnership with the Metropolitan Police Service (MPS). The aim of the project has been to develop new methods and applications in space-time analytics and emergent network complexity, in order to uncover patterning and interactions in crime, policing and citizen perceptions. The work carried out throughout the project will help inform policing at a range of scales, from the local to the city-wide, with the goal of reducing both crime and the fear of crime.

The CPC project is timely given the tremendous challenges facing policing in big cities nationally and globally, as consequences of changes in society, population structure and economic well-being. It addresses these issues through an intelligent approach to data-driven policing, using daily reported crime statistics, GPS traces of foot and vehicular patrols, surveys of public attitudes and geo-temporal demographic data of changing community structure. The analytic focus takes a spatio-temporal perspective, reflecting the strong spatial and temporal integration of criminal, policing and citizen activities. Street networks are used throughout as a basis for analysis, reflecting their role as a key determinant of urban structure and the substrate on which crime and policing take place.

The project has presented a manifesto for ‘intelligent policing’ which embodies the key issues arising in the transition from Big Data into actionable insights. Police intelligence should go beyond current practice, incorporating not only the prediction of events, but also how to respond to them, and how to evaluate the actions taken.

Cutting-edge network-based crime prediction methods have been developed to accurately predict crime risks at the street segment level, helping police forces to focus resources in the right places at the right times. Methods and tools have been implemented to support senior offices in strategic planning, and to provide guidance to frontline officers in daily patrolling. To evaluate police performance, models and tools have been developed to aid identification of areas requiring greater attention, and to analyse the patrolling behaviours of officers. Methods to understand and model confidence in policing have also been explored, suggesting strategies by which confidence in the police can be improved in different population segments and neighbourhood areas.

A number of tools have been developed during the course of the project including data-driven methods for crime prediction and for performance evaluation. We anticipate that these will ultimately be adopted in daily policing practice and will play an important role in the modernisation of policing. Furthermore, we believe that the approaches to the building of public trust and confidence that we suggest will contribute to the transformation and improvement of the relationship between the public and police.
INTRODUCTION

CHALLENGES FACING DIGITAL POLICING

Crime and disorder are long-standing societal problems which continue to blight the emotional and economic well-being of citizens. Predicting, preventing and mitigating crime and disorder is fundamental to the evolution of modern societies and the cities they live in.

Policing is crucial to public safety. London’s Metropolitan Police Service (MPS) responds to over 10,000 calls every day, and is also responsible for a wide range of crime prevention duties. It faces huge challenges, arising not just from resourcing issues but also the very way we think about the role of policing.

The mission of policing is evolving, with issues such as public confidence gaining increased recognition as important police performance metrics. The improvement of confidence is a key priority for policymakers such as the Mayor’s Office for Policing and Crime, and is seen as a crucial factor in crime prevention and detection. The fact that recent achievements in crime reduction have not been reflected in public confidence suggests an enduring ‘reassurance gap’ between successful policing and the public perception of it.

Ongoing reductions in funding are placing increased strain on police resources: the MPS, for example, must make 20% efficiency savings by 2020. This is not accompanied by any reduction in targets, and indeed the MPS must also achieve a 20% decrease in crime and a 20% improvement in public confidence over the same period. ‘More for less’ is the mantra for policing today in London.

BIG DATA IN POLICING

While many aspects of police resourcing are becoming increasingly constrained, however, there is one respect in which forces are becoming dramatically richer: access to digital data. Not only is crime recorded more comprehensively than ever before, but technological advances such as GPS tracking offer unprecedented insight into the way that policing itself is undertaken. Following the launch of a £2 million scheme in 2010, for example, MPS police radios record officer locations at 5-minute intervals, while vehicle locations are logged every 15 seconds.

These data sources are complemented by a number of others which offer insight into the key issues of public perception and engagement. The Crime Survey for England & Wales provides information about the experience of crime, while the MPS Public Attitude Survey and Victim Survey focus particularly on issues of confidence in the London context. When combined with geodemographic data, these

Figure 1: Trends in the perception of crime levels show that, paradoxically, people believe that crime is increasing at a national level, but not in their local area (Source: British Crime Survey).
sources allow the influence of the potentially huge number of factors that shape criminal activity and public perceptions to be explored.

A number of recent developments, broadly themed around the concept of ‘predictive policing’, testify to the potential of data-driven law enforcement. There remain, however, a number of limitations to these techniques, particularly with respect to their integration in real-world policing. In many instances these may arise because of a siloed approach to crime reduction that brings focus to one element of policing without considering the inter-dependencies between its various aspects.

The success of any algorithmic solution depends crucially on how it translates into actionable policing: the success of a predictive algorithm, for example, becomes immaterial if the ensuing police response is insufficient to prevent the anticipated crimes. Furthermore, little is understood about the impact on public perception of geographically focussed policing strategies; yet this is a crucial concern, given the ever-increasing pressure to improve public confidence.

These issues can only be addressed by using the datasets available to the police in an integrated way, modelling and accounting for the significant inter-dependencies between them. Criminality and policing are inter-related phenomena which occur against a mosaic of different neighbourhood contexts. Close examination and interpretation of how the detailed patterns of police activities relate to the space-time characteristics of criminal incidents is required not only for effective policing, but also for effective reassurance of the public.

Ensuring that data are used intelligently is thus key to improving the efficiency and effectiveness of operational practice in the era of digital policing. Innovation in best practice through collaborative research has a crucial role to play in improving the exploitation of data, and provides the setting for this project.

INTELLIGENT DATA-DRIVEN POLICING

The CPC project was set up to develop a fully-integrated approach to data-driven policing, with particular emphasis on the spatial and temporal characteristics of crime, policing and citizen reassurance. Measuring, modelling and predicting the interactions between these amounts to an intelligent and holistic approach to policing in the digital age.

The CPC project has developed a manifesto for ‘intelligent policing’ which embodies four inter-related issues that arise in the course of the journey from data collection to final policing outcomes. Each issue raises specific research questions that have been examined throughout the project.

First, we propose that data-driven tools must be easy to use and translate straightforwardly into police action. The outputs of many existing products are far from intuitive: the large ‘boxes’ identified by many predictive algorithms, for example, contain many road sections and it is often unclear exactly where officers should be deployed. To ensure effective use, tools should be designed with their operational implementation explicitly in mind.

Our second key principle is that, for tools to be successful in improving police efficiency, accuracy of prediction is paramount. This requires refinement of analytical techniques for specific policing contexts, as well as the selection of appropriate units of analysis, if police resources are to be directed with the greatest precision.

Our third point concerns the management of resources. Many police activities involve the movement and placement of officers, either in response to incidents or in anticipation of them. The volume and spatial diversity of these demands means that deciding how these tasks are allocated and structured is a complex problem, and it is vital to understand how the tasking of officers can be coordinated as efficiently as possible.

Finally, we emphasise the role of feedback in the evaluation and refinement of policing strategies. In order to better understand the effectiveness of new approaches, it is necessary to know: a) whether assignments were properly carried out by officers, and b) whether they had their intended effects. The use of tracking technology to monitor both compliance and efficacy can play a vital role in developing an evidence base.
OUR APPROACH

The CPC project is fundamentally inter-disciplinary, incorporating approaches from geoinformatics, crime science, geography, computer science and mathematics. To our knowledge, it is the first attempt to combine approaches from these fields, and to address these challenges in a holistic manner.

Many of the methods used in the course of the project emanate from complexity science. The research takes an integrated spatio-temporal perspective, reflecting the strong spatial and temporal integration of all the three aspects involved: crime, policing and citizens.

Network science, as a crucial cross-cutting theme of the project, provides both a framework for spatio-temporal analysis and a convenient representation of urban structure. A key aspect of our project is that the tools and techniques we have produced are street network based: we believe this representation not only allows for greater accuracy, but is also advantageous from the perspective of implementation. In addition to this, methods from Big Data analytics, including machine learning, statistical analytics and agent-based simulation, have been used to develop the algorithms and tools.

All of the research has been carried out in close collaboration with the MPS, which has provided support in the form of data and guidance concerning current policing challenges. A range of data sources were used on the project, including incident logs, tracking data and public surveys. The recent opening of the JDI Research Laboratory – a £1m secure data facility – means that these datasets can be analysed on-site at UCL.

In addition to our scientific findings, the strong practical focus of the project has led to the development of several tools for use in real-world policing. These include our network-based predictive mapping algorithms and patrol analysis techniques, both of which have been implemented for real-world use. In conjunction with other tools for patrol strategy development and public confidence analysis, these form a suite of tools that can be used to support data-driven policing in an operational context.

Figure 2: In London, the Mayor’s Police and Crime Plan sets ambitious objectives for various aspects of police performance.

<table>
<thead>
<tr>
<th>7 priority crimes</th>
<th>Public confidence</th>
<th>Total cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>20%</td>
<td>20%</td>
<td>20%</td>
</tr>
</tbody>
</table>

Figure 3: The spatio-temporal patterns formed by crime, policing and citizenship activity form dynamic, interdependent networks.
Years of empirical research have demonstrated that the occurrence of crime displays a number of regularities in space and time. Crime occurs disproportionately at certain times and locations, in a way which can be reconciled with theories of offender behaviour. The existence of these regularities has substantial implications for policing, since they imply that crime is to some extent ‘predictable’. If the regularities in question can be accurately modelled, this raises the possibility that the spatio-temporal distribution of crime risk can be forecasted.

**MOTIVATION**

The idea that crime can be predicted is clearly of great potential value to policing. In particular, it provides a basis upon which police can take a proactive approach to resource deployment, intervening in vulnerable locations before crime occurs. Placing officers at the locations and times at which crime is most likely focuses policing resources where they are most needed, resulting in improved efficiency, reduced crime rates and greater public satisfaction.

**SPACE-TIME PATTERNING IN CRIME DATA**

At their simplest, the regularities observed for crime relate to the basic fact that overall levels or crime vary in space and time: some places are simply more risky than others. In addition to this, however, strong interaction effects are frequently observed. Most prominent among these is the phenomenon of space-time clustering, which refers to the tendency of events which are close in time to also be close in space. This is most distinctively manifested in ‘near repeat’ victimisation, in which locations near the site of a recent offence are themselves at heightened risk for some time period after the incident (see Figure 1).

**MODELLING CRIME PATTERNS**

Two key theoretical concepts have been proposed to explain the spatial and temporal patterning of crime incidents. The first – risk heterogeneity – states that risk varies because of differences in the underlying factors which influence crime: some places are simply more prone to crime than others. This property is generally static or slowly changing over time. The other principle – event dependency – seeks to explain clustering in particular by stating that the occurrence of a crime actively increases the probability of further incidents in the vicinity. This effect is temporary, but can last for some time (several weeks in the case of burglary).

**AN EARTHQUAKE MODEL APPLIED TO CRIME**

The self-exciting point process (SEPP) model originated in modelling earthquake aftershocks, but has recently been applied to describe crime events. The SEPP model combines the two theories discussed above into a single framework: crimes occur against a slowly-varying background risk landscape (risk heterogeneity) and every crime that occurs has the potential to trigger further crimes in its vicinity (event dependence). The background and triggering profiles can be determined using a machine learning

![Figure 1: Relative frequency of pairs of burglary crimes in Camden that are within 100 metres and the specified time difference of one another. The blue region indicates crimes which occur more frequently than would be expected in the absence of clustering.](image-url)
algorithm, after which they are combined to forecast the appearance of the combined risk landscape at some future time. Figure 2 shows an example: the SEPP generates a continuous risk surface, which can then be transformed onto a square grid, with the most risky cells highlighted.

**APPLYING THE SEPP TO DATA**

We applied the SEPP to recorded burglary data from the London borough of Camden in an 8 month period commencing in August 2011 (1993 crimes). The triggering profile is shown in Figure 3 and indicates that a burglary is associated with an elevated risk within a radius of around 200 metres for a time period of 60 days. This profile varies by location and crime type; the SEPP model is tailored to the specific situation.

**IMPLICATIONS**

The SEPP model provides a customisable approach to crime prediction, incorporating two key criminological theories. It is straightforward to train the model using historic crime records and the triggering profile gives insight into the underlying crime dynamics. The predictive accuracy is higher than popular alternative methods, suggesting that such methods offer an effective way to target policing interventions.

Figure 2: (Top) a continuous prediction heatmap generated by the SEPP. Darker red indicates higher risk. (Bottom) the top 10% of grid squares for the same prediction.

Figure 3: The crime triggering profile in time and space for burglaries in Camden.
PREDICTION ON STREET NETWORKS

KEY POINTS

Aims To develop a street network-based algorithm for the prediction of urban crime.

Methods A kernel-based approach was adapted to apply to network space, and used to identify street segments at high crime risk.

Findings The network-based approach leads to substantial gains in predictive accuracy, as well as providing outputs in a form which is convenient for patrol planning.

BACKGROUND

The majority of predictive algorithms developed to date are either grid-based or produce risk estimates for regions of a map, such as circles. While it is certainly possible to predict crime at these levels, however, there are other representations of space which may be more appropriate. In particular, using the street network as the spatial basis for prediction has a number of potential advantages in terms of both accuracy and usability.

ADVANTAGES OF NETWORK-BASED APPROACH

One of the primary benefits of using the street network is its spatial granularity. The grid squares typically used for prediction are relatively large – 250m x 250m, for example – and contain many roads and features, making it difficult to identify exactly where risk lies or where officers should patrol. Street segments, in contrast, are well-defined micro-units, which allow risk to be estimated with much greater precision. Furthermore, since officers patrol by following defined routes along streets, network-based risk maps are easier to interpret in practice.

RISK DIFFUSION

There are also reasons to anticipate that the network will play a role in the spread of crime itself. Much of the theory on which predictive methods are based refers to the way in which offenders perceive and navigate their environment, committing offences near places that they know or the locations of previous crimes. Since the network is a key determinant of urban structure, and of the proximity of places in particular, it is natural to expect that it will influence the distribution of crime.

NETWORK-BASED MODEL

To explore the potential of these ideas, we developed a predictive model of crime which is fully network-based in terms of both its mechanism and output. The model builds on previous kernel-based approaches: a prospective risk ‘surface’ is computed by summing contributions from nearby previous crimes, weighted according to how recently they occurred. The crucial difference in our model is that the kernels are computed in network space (see Figure 1), reflecting the notion that risk is transmitted down streets rather than uniformly through space.

Figure 1: Spatial kernel function implemented in network space (represented by black lines). A kernel is placed at all locations of previous crimes.
PROSPECTIVE RISK MAPS

We also developed a novel training protocol for the algorithm, which identifies the optimal kernel parameters for the model with respect to predictive accuracy. Using these parameters, the model can be used to compute a prospective risk surface for crime on any given day, which, in turn, allows the highest-risk streets to be identified. An example of a risk map produced by this method is shown in Figure 2, which also shows the output of the equivalent grid-based method for comparison. The difference between the maps is clear to see: a number of high-risk streets are located outside the highest-risk cells, and vice versa.

PREDICTIVE ACCURACY

We compared the predictive performance of the two approaches by examining their ‘hit rates’ when applied to the same underlying crime data. In computing these rates, coverage is measured in terms of network length, thereby controlling for variation in street length across grid cells. As shown in Figure 3, the network-based method out-performs the grid-based equivalent by a factor of between 1.5 and 2 for the majority of coverage levels considered.

Figure 2: Comparison of predictive risk maps, showing a) network-based, and b) grid-based approaches. In both cases, the top 5% most risky units are highlighted.

IMPLICATIONS

Our results indicate that using the street network as the spatial basis for prospective mapping leads to significant improvements in predictive performance when compared with grid-based approaches. This fact alone suggests that such algorithms offer an improvement on the existing systems used within operational policing. Given that predictions expressed in this form also offer a number of practical advantages – the maps are easily understood and especially conducive to patrol planning – there appears to be a clear case for the adoption of the network-based approach throughout predictive policing.

Figure 3: Comparison of predictive ‘hit rates’ achieved with network- and grid-based approaches.
A vital component of prospective mapping is the process of evaluating the performance of predictive methods. As well as quantifying expected performance, such analysis provides a means of comparing the capabilities of different predictive approaches. Until recently, however, crime analysts have had few tools at their disposal to aid them in assessing and comparing the many available prediction methods. The resulting lack of robust selection criteria has hampered the adoption of such methods in real operational environments.

In the majority of work to date, predictive accuracy—the extent to which the locations of future crimes are correctly identified—has been used as the sole measure of a method’s performance. However, this alone fails to capture a number of other aspects which are of material importance to the success of an approach in a real-world setting. The ease with which predicted locations (hotspots) can be policed, for example, is a very significant issue for police officers: if an intervention cannot be applied, the predicted crimes cannot be prevented. To address these issues, we have formulated an evaluation framework which combines a number of measures to give a comprehensive view of the performance of a predictive method in an operational context.

Key Points

Aims To develop a robust toolkit for the evaluation of crime prediction methods.

Methods We propose four metrics which capture various aspects of performance, with emphasis on real-world implementation and usability.

Findings Application of the framework reveals strengths and weaknesses in popular predictive approaches, and can aid the selection of appropriate methods in various operational settings.

EVALUATION FRAMEWORK

In our evaluation framework, four properties of predictive maps are considered:

- **Predictive accuracy** – the proportion of crime captured within the predicted locations. We also incorporate a significance test that allows the difference in accuracy between two methods to be quantified statistically.

- **Compactness** – how concentrated and connected the areas identified are. Compactness reflects the intuitive idea that less dispersed areas are easier to patrol and therefore operationally preferable (see Figure 1).

- **Dynamic variability** – the extent to which the predicted locations change between consecutive predictions. Our metric measures the timescale of response to changes in crime patterns, thereby distinguishing between conservative methods that simply reflect long-term risk, and those which are highly variable from day to day (see Figure 2).

![Figure 1: Illustration of compactness, with high-risk areas coloured grey. The hotspots in the left-hand figure are more compact than those on the right.](image1)

![Figure 2: Dynamic variability for consecutive days: grey indicates repeated hotspots, blue indicates emerging hotspots and red indicates disappearing hotspots.](image2)
Complementarity – the extent to which different methods detect the same crimes or provide a supplement to one another is measured by the complementarity index.

**PREDICTIVE METHODS**

We used our framework to examine the performance of four prominent predictive approaches. We performed a case study using data from London borough of Camden, examining three crime types, chosen to reflect differing levels of sparseness in the underlying patterns.

**RESULTS**

Our results (see Table 1) demonstrate that the various methods considered here each display a number of strengths and weaknesses with respect to their operational utility. While some methods are capable of producing very high predictive accuracy, for example, their low compactness scores imply that the locations they identify may not be easy to patrol. Furthermore, dynamic variability reveals that some methods produce predictions which remain essentially unchanged for periods of up to one week.

A number of more general observations can also be made. There appears to be no correlation between variability and either accuracy or compactness, suggesting that highly dynamic methods offer little ultimate benefit. Furthermore, complementarity shows that each method is successful at identifying, exclusively, a substantial number of crimes outside the ones jointly captured by the other methods (see Figure 3), particularly for violent crimes and burglaries. This suggests that an ensemble method, combining multiple predictions, may be the best solution in these cases.

**IMPLICATIONS**

The framework we have developed allows predictive approaches to be evaluated in a significantly more comprehensive way than is currently done, with particular emphasis on their operational utility. Our case studies reveal that predictive approaches display a range of strengths and weaknesses when these aspects are taken into account, implying that the choice of method must necessarily involve a number of trade-offs. Our framework allows these to be assessed quantitatively, thereby equipping police analysts with the tools required to select approaches in an informed way based on operational needs.

**Table 1: Evaluation metrics for Camden crime prediction at 20% coverage level. Bold indicates the greatest mean value over 100 days’ prediction.**

<table>
<thead>
<tr>
<th>Crime Type</th>
<th>Method</th>
<th>Accuracy</th>
<th>Compactness</th>
<th>Variability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hit rate</td>
<td>CI</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Shoplifting</td>
<td>PSTSS</td>
<td>81.3</td>
<td>27.6</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>PKDE</td>
<td>74.3</td>
<td>29.8</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>SEPP</td>
<td>91.5</td>
<td>20.1</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>PHotspot</td>
<td>85.1</td>
<td>27</td>
<td>0.37</td>
</tr>
<tr>
<td>Violence</td>
<td>PSTSS</td>
<td>46.5</td>
<td>20</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>PKDE</td>
<td>51.7</td>
<td>19.5</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>SEPP</td>
<td>59.7</td>
<td>19.8</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>PHotspot</td>
<td>52.2</td>
<td>19.9</td>
<td>0.32</td>
</tr>
<tr>
<td>Burglary</td>
<td>PSTSS</td>
<td>34.4</td>
<td>22</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>PKDE</td>
<td>38.8</td>
<td>24.2</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>SEPP</td>
<td>47.4</td>
<td>26.3</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>PHotspot</td>
<td>34.9</td>
<td>23</td>
<td>0.3</td>
</tr>
</tbody>
</table>

**Figure 3: Venn diagram showing the total number of crimes identified by each method at a fixed coverage of 20% in Camden.**
Much crime prevention activity depends, at some level, on the ability of police officers to deter crime by being physically present in a place. This idea forms the basis for a significant proportion of police activity, with visible patrol – one of the few tactics available to police that can be used to address crime problems on a day-to-day basis – a primary example of this. In particular, patrol plays a crucial role in ‘predictive policing’ approaches, since it typically constitutes the primary tactical response: officers are sent to the predicted locations in order to discourage or interrupt the anticipated crimes.

Despite its importance, however, the question of whether patrol does indeed deter crime has not been addressed in quantitative terms: put simply, there is a lack of evidence concerning whether patrol really ‘works’. The reason for this is largely technical: traditionally, there has been no means of systematically recording the locations of officers, meaning that it has been impossible to test whether their presence affects crime. The recent proliferation of GPS technology, however, has removed this barrier by allowing officer movements to be logged in their entirety. In this part of the project, we used tracking data of this type from the MPS to perform the first large-scale quantitative study of the deterrent effect of policing.

In our initial analysis, we explored the temporal relationship between patrol visits and calls for service. Using a technique previously applied to study repeat victimisation, we examined whether the two events occurred closer together – or further apart – than would be expected if they were unrelated. Figure 1 shows the intervals between the two event times for street segments in Camden, with the black line showing the expected distribution if the events were independent. As can be seen, short positive intervals (which correspond to cases where patrol visits are followed by incidents) occur less frequently than would be expected, which implies that police presence does discourage crime.

To test these effects in a more sophisticated way, we also used an epidemiological approach known as survival analysis. This involves examining the ‘survival times’ associated with each patrol visit: the time elapsed until the next crime occurs on the street segment visited (shown for Camden in Figure 2). By comparing these to what would be expected if no patrol had occurred, the effectiveness of patrol can be quantified: do streets survive for longer than they would otherwise have done?
BASELINE ESTIMATES

Estimating expected survival times is a technical challenge, however, since the underlying level of risk varies across segments and times. To address this, we developed a set of Monte Carlo-based approaches by which the typical time-to-next-crime can be estimated for any street segment, at any time. These times can be compared statistically to the observed intervals between police visits and calls.

SURVIVAL RESULTS

In Figure 3, we show the results of a regression model for the ‘hazard rate’: the instantaneous risk of crime as time elapses after a patrol event. The plotted line shows the deterrent effect: its distance below the zero line shows the decrease in risk, compared with what would be expected in the absence of patrol. These results imply that patrol does indeed have a sustained deterrent effect, but that it is small and only marginally statistically significant.

IMPLICATIONS

This research contributes to the evidence base concerning the fundamental policing tactic of visible patrol. The finding that patrol does act as a deterrent is encouraging from the perspective of everyday policing, but this should be tempered somewhat by the relatively modest size of the effect. This implies that the importance often ascribed to patrol may be overstated, which has significant potential consequences in terms of how routine policing should be done. It should be stressed, however, that additional research is required to address more subtle questions: how frequently patrol should be applied, and whether it acts differentially across crime types and areas. Ultimately, though, research of this type can be used to inform the design of improved patrol strategies, via which the police can increase the efficiency with which they prevent crime.
The ability to accurately replicate how police navigate around the city is of crucial importance in answering what-if questions, such as:

– How does changing the number of vehicles on patrol affect street coverage?

– How do locations of police stations affect the time needed to reach crime scenes?

It also gives insights into any regularities in police behaviour that might impact on their preventive capabilities. Standard route planning algorithms fail at this task as they cannot replicate sub-optimal route choices, such as those that are frequently required in the course of policing.

ARE POLICE ROUTES OPTIMAL?

Standard route planning algorithms are based on the assumption that drivers are 100% rational in their behaviour. When given a journey destination, they would find possible routes to reach the destination and always pick the one that incurs the smallest cost (in terms of distance, time, etc.). However, as is the case of most drivers, police choose routes that cannot be fully explained within the rationality framework. As shown in Figure 1, they tend to follow paths that are slightly longer than the shortest possible alternatives. This might be explained by their limited spatial knowledge, traffic, or monitoring activities that purposely avoid major roads.
SIMULATING POLICE JOURNEYS

We simulated police journeys as sequences of their preferred routes. This involved representing the street network in an aggregated form where streets belonging to the same route were collapsed into a single node. Links between nodes were drawn if the nodes contained adjacent streets. An exemplary such network is shown in Figure 3a. Journeys predicted using our model, as the one shown in Figure 3b, incorporated data-driven routing preferences of the police, which lead to significant improvements in accuracy when compared to off-the-shelf routing algorithms.

IMPLICATIONS

Our proposed model shows significant improvements over existing methods in replicating the routing behaviour of police officers. This provides justification for its potential use as a planning tool for police resourcing. By simulating journeys under different assumptions, the real-world implications of potential policy changes can be explored in advance, allowing police decision-makers to plan in an evidence-based way.
CHARACTERISING FOOT PATROL BEHAVIOUR

KEY POINTS

**Aims** To characterise and classify the movement patterns of foot patrol officers.

**Methods** Using officer GPS traces, spatio-temporal regions of high patrol intensity were identified. Officer behaviours were then classified according to their visits to these locations.

**Findings** Officer activity clusters around certain prominent locations, and distinctive behavioural signatures can be identified in their visits to these.

BACKGROUND

The things people do in space and time have long been a research topic in behavioural and socio-economic studies, particularly in relation to highly dynamic urban environments. In this field, the term ‘activity pattern’ is used to describe the movements which groups of people take in the course of their routine daily activities. These activities are intrinsically linked to the places and times at which they are undertaken, to the extent that it can be said that ‘where, when and how long you stay is who you are’.

ACTIVITY PATTERNS IN POLICING

The study of activity patterns has particular value for policing since, while coverage is clearly a crucial operational issue, relatively little is known about how officers make decisions during self-directed activity. In the context of policing, and foot patrol in particular, such findings have potential operational relevance. Identifying places and time periods with distinctive patrol patterns, as well as grouping officers who share similar patterns, is of use for both performance evaluation and for identifying aspects of behaviour which could be improved.

BEHAVIOURAL CLASSIFICATION

In our research, we have proposed a methodological framework for uncovering space-time activity patterns from individuals’ movement trajectory data, which can then be used to segregate users into subgroups according to the similarity between their patterns. This is designed to be applied to newly-available datasets which collect the ever-changing position of moving individuals with high spatial and temporal resolution. The Automatic Personnel Location System (APLS) used by the MPS to record officer movements using GPS is one such source, and provided the basis for our work.

SPATIO-TEMPORAL REGIONS OF INTEREST

In the proposed framework, APLS traces are first map-matched onto the street network to identify the street segments that the officers truly visited. The places and times at which particularly high levels of officer presence were observed are then identified using a network-based variant of the clustering algorithm DBSCAN. These regions of space-time are defined as Spatio-Temporal Regions of Interest (ST-ROIs), and represent locations which feature particularly prominently in patrol behaviour (Figure 1).

Figure 1: During the study period, 28 ST-ROIs are detected for foot patrol officers by space-time DBSCAN – these are identified by colour here.
GROUPING OFFICERS

Once ST-ROIs have been identified, individual officers’ activity patterns can be expressed in terms of their visits to these locations. An individual’s behaviour is defined as his/her profile of time allocation to the ST-ROIs s/he visited, and can be considered to be a ‘signature’ of patrol activity (Figure 2). By applying a hierarchical clustering approach to these profiles, officers can be partitioned into subgroups based on the similarity of their activities in space and time (see Figure 3).

SUMMARY OF THE ACTIVITIES

When the officer subgroups are examined in turn, a qualitative understanding of their characteristic behaviours can be gained. One group of officers, for example, can clearly be seen to be involved in intensive patrol activity overnight in a location which is known to be a centre of the night-time economy. Another group clearly corresponds to a specialist operation at a location outside Camden, when officers are seen to deploy for long stints of patrol after beginning at a Camden station.

IMPLICATIONS

The application of our framework has the potential to offer unprecedented insight into the micro-level behaviour of police officers during routine patrol. The framework extends traditional ideas of time budget allocation, and is capable of profiling the activity patterns of officers in both space and time by defining a new moving behavioural similarity metric. Since the clustering method explains the semantic meaning of different behaviours – activities are mapped in terms of visits to particular landmarks – the findings are readily interpretable by commanding officers. Findings such as these could be used to suggest behavioural modifications which could lead to more efficient coverage.

Figure 2: Simplified representation of two example officers’ movements, showing (a) trajectories in space-time; (b) simplified representation showing the visiting sequence of ST-ROIs.

Figure 3: Taxonomy tree showing the clustering of officers with different patrol patterns (ID numbers randomised).
STRATEGIC PLANNING FOR OFFICER TASKING

KEY POINTS

Aims To provide a tool to explore the impact of changes to police operations.

Methods An agent-based simulation model for officer behaviour and tasking was developed, based on insight gained for active officers.

Findings The model replicates real-world officer behaviour in terms of the spatial distribution of coverage, suggesting that it has potential use as a real-world decision support tool.

BACKGROUND

As part of the development of policing, it is natural for senior officers to consider the potential of changes in operational practice to improve the efficiency of policing. These changes might be technological, such as the adoption of handheld devices, or behavioural, such as the refinement of tasking protocols. Variations in resource levels can impact the ability of officers to provide service, while terrorist attacks or special events drastically affect the set of responsibilities officers must handle. These cases represent material changes to the way that policing is done. A crucial task in assessing the potential value of such changes is estimating their likely impact on performance, so that decisions can be taken in an informed way. The complexity of policing practice, however, means that this is a very difficult task: the potential for knock-on effects and feedback loops means that such questions cannot be answered simply.

AGENT-BASED MODELLING

One analytical technique which has substantial potential value in such situations is agent-based modelling. Agent-based modelling is a computer simulation method in which artificial populations are endowed with realistic behavioural rules and situated within an environment, within which they interact with one another. In simple terms, it involves the simulation of artificial ‘worlds’, the development of which can be examined with unlimited granularity. By changing the behavioural rules or parameters, the potential impact of these changes can be explored: the method provides a means of examining ‘what if’ questions in a very detailed way. In the context of policing, such a simulation can be used to explore the impact of potential operational changes on performance indicators such as response time and coverage.

Figure 1: The decision flow for a simulated officer in ‘Responding’ status.

Despatched to incident?

Yes

No

Patrol

Go to incident site (ignore traffic laws)

Deal with incident

Need Transport Vehicle?

No

Yes

Wait until Transport Vehicle arrives

Need Transport Vehicle?

No

Yes

Return to station to make a report

Figure 1: The decision flow for a simulated officer in ‘Responding’ status.
SIMULATING TASKING

In order to explore these questions, we developed an agent-based model for the behaviour and tasking of police officers. The construction of the model was informed by consultation with police officers, and incorporated several aspects: the dispatch process, the travel of officers to incidents, and self-directed patrol behaviour. Simulated officers act according to decision trees (see Figure 1) and the aim of the model is provide a comprehensive simulation of the day-to-day behaviour of a police force.

CAMDEN CASE STUDY

In order to establish that the model produced realistic behaviour, and to examine its potential as a policy tool, we applied the model in the context of the London borough of Camden. We used real-world data on calls for service, so that simulated officers were required to respond to calls exactly as they were in the real world. To establish validity, we examined whether the movement patterns generated were similar to those of real Camden officers in the period in question. The distribution of road usage – a distinctive feature of real-world patrol – was broadly in agreement (see Figures 2 and 3), and a significant improvement over corresponding null models.

IMPLICATIONS

Modelling tools based on agent-based simulation have considerable potential as policy tools because they provide a means to explore extremely complex systems in an objective and transparent way. Our results suggest that our model is a useful representation of real world policing, and that it therefore represents a valid basis for such a tool. As well as refining the model in order to achieve closer correspondence with reality, we will use it to explore a number of real-world policy questions relating to potential changes in policing practice.
Police patrol occupies a central place in crime control efforts. In particular, hotspot patrolling – in which effort is focussed on small geographical units with high crime intensity – has gained particular prominence as a means of deterring potential crime and increasing public perception. The issue of how such patrols can be most efficiently operationalised, however, presents a significant logistical challenge, especially when police resources are limited and hotspots are many.

In most operational contexts, hotspot patrolling is implemented by tasking officers to randomly rotate between hotspots. However, randomised strategies have a number of shortcomings, as they omit the peculiarities and challenges of daily police patrol, such as the desire to minimise the average time lag between two consecutive visits to hotspots, while also coordinating multiple patrollers and imparting unpredictability to patrol routes. To address these issues, and to ensure that patrol is performed as efficiently as possible, it is necessary to develop a cooperative routing strategy.

### MEASURES

Before any new strategy can be developed, it is necessary to express the objectives of police patrol in quantitative terms. However, there is a lack of systematic investigation of the relevant measures. In the first stage of this research, we explored the question of what makes a good police patrol routing strategy, and proposed a number of guidelines and measures, shown in Table 1.

### ONLINE BAYESIAN ANT-BASED PATROLLING STRATEGY

We developed a routing strategy, Bayesian Ant-based Patrolling Strategy (BAPS), according to the proposed guidelines (Figure 1). The main idea of BAPS is to use ‘pheromones’ to record visit history on hotspots, which can then be used to prioritise demand. The algorithm uses Bayesian decision-making to incorporate multiple factors, and performs one-step routing each time.

### Table 1. Guidelines for police patrol routing strategy

<table>
<thead>
<tr>
<th>Measure</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency (E)</td>
<td>To cover hotspots regularly and fairly</td>
</tr>
<tr>
<td>Flexibility (F)</td>
<td>To cover hotspots that have varying degrees of weights</td>
</tr>
<tr>
<td>Scalability (S)</td>
<td>To be applicable to patrolling in different areas (spatial scalability) and different numbers of patrollers (team scalability)</td>
</tr>
<tr>
<td>Unpredictability (U)</td>
<td>To keep the patrol routes unpredictable</td>
</tr>
<tr>
<td>Robustness (R)</td>
<td>To remain effective patrolling when some patrollers are dispatched for emergencies</td>
</tr>
</tbody>
</table>

Figure 1. From guidelines to BAPS.

### Online Bayesian Ant-based Patrolling Strategy
CASE STUDY

We examined the performance of BAPS using a bespoke multi-agent modelling framework (see Figure 2), with real-world crime data from the London borough of Camden used as a case study. Crime hotspots were defined as the 5% of segments with the highest crime density level (see Figure 3), and were divided into 5 levels. An existing deterministic patrolling strategy known as CCPS was used as a benchmark.

RESULTS

The performance of BAPS is compared against that of CCPS in terms of the 5 key metrics (See Table 2). In the experiments, 30 patrollers started from 6 stations. In the normal scenario, they only patrolled, whereas in the emergency scenario, they also responded to emergency calls when needed. The results show that BAPS outperforms CCPS across all 5 performance measures.

IMPLICATIONS

This research represents a significant step in the development of intelligent patrolling, which has the potential to substantially improve the operational efficiency of targeted interventions. The performance measures introduced allow patrol to be evaluated in objective and quantitative terms, meaning that behaviour can be refined in an evidence-based way. By adopting a probabilistic framework, the cooperative BAPS strategy introduced achieves significant performance improvement, suggesting that it has the potential to form the basis for an effective real-world protocol. Future work will consider how this can be implemented in a practical context, and integrated alongside vehicle patrol.

Table 2. Comparison of CCPS and BAPS performance

<table>
<thead>
<tr>
<th></th>
<th>E (1700)</th>
<th>F (1623)</th>
<th>U (2055)</th>
<th>S (1.037)</th>
<th>R (3.30%)</th>
<th>Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAPS</td>
<td>1700</td>
<td>1623</td>
<td>2055</td>
<td>1.037</td>
<td>3.30%</td>
<td>-16.60</td>
</tr>
<tr>
<td>CCPS</td>
<td>2039</td>
<td>2030</td>
<td>497</td>
<td>0.996</td>
<td>4.10%</td>
<td>-20.05</td>
</tr>
</tbody>
</table>

E- Efficiency; F – Flexibility; U – Unpredictability; S: (Team) Scalability; R - Robustness

Figure 2. Schematic diagram of BAPS.

Figure 3. Camden hotspot map.
TRUST AND CONFIDENCE IN POLICING

KEY POINTS

**Aims** To provide a theoretical and empirical framework for investigating and improving public trust in policing.

**Methods** A mental models approach was applied in conjunction with interviews conducted in London.

**Findings** The approach offers insight into the factors that influence trust, and reveals a number of misconceptions amongst both experts and the public. These can be used to inform strategies to improve trust.

BACKGROUND

A growing number of studies report lower levels of public trust and confidence in governments and their institutions and public services, which influence public engagement, co-operation and participation which all exist at the heart of democratic institutions. Public trust in policing is no exception; evidence shows that confidence is shrinking. In the UK, where the ideological emphasis is on policing by consent, this is particularly problematic and thus ‘promoting public confidence’ in policing has been a top priority of the government agenda.

MOTIVATION

An increasing number of studies and surveys attempt to investigate and measure trust and confidence in policing. Not only is there no conceptual clarity between the two terms and how these are used in the policing context, but there is also a complete lack of a theoretical and empirical framework on which investigations are based. This raises significant concerns about the validity of the results and subsequently the effectiveness of measures and policies which attempt to improve public trust and confidence in policing. Our research attempts to address this gap.

THE ROLE OF THE TRUSTEE ATTRIBUTES

Trust is a complex phenomenon, which is highly context-dependent and incorporates a number of factors. In many models, including that used by our team – see Figure 1 – an individual’s willingness to trust is dependent on both their own personal attributes and those of the trustee. The influence of these factors is of particular relevance in the context of policing. It is natural to assume that trust perceptions are not universal, and are influenced by factors such as cultural or educational background, prior experiences, misconceptions and the lack of a shared public understanding of police practices.

Figure 1: Trust Model
THE MENTAL MODELS APPROACH

The mental models approach provides a framework for uncovering the decision processes of individuals. It is based on the idea that human memory is organised into ‘schemas’, which describe how an individual perceives a problem, depending strongly on previous personal experiences, knowledge, activating stimuli, and other factors. Depending on their complexity, mental models may consist of one or more schemas, which influence decisions and the way that individuals perceive the world. The mental models approach provides a systematic way to uncover these, the concepts that are included and the vocabulary people use to describe them. In addition, it can also reveal misconceptions and knowledge gaps that should be corrected.

LONDON STUDY

We conducted 25 interviews with both experts and members of the public in London (with almost half of the subjects from the borough of Barking & Dagenham and the rest from wider London). Analysis of our preliminary results shows – perhaps surprisingly – that there is no common and shared understanding of trust and confidence in policing amongst experts. In other words, the expert mental models of experts in this topic vary significantly, as do the issues that they perceive to matter most to the public. Furthermore, the trustee attributes that are used in various surveys to measure trust (e.g. perceived legitimacy, altruism) are not necessarily present in the expert mental models captured in our study. In addition to this, the public mental models also reveal significant gaps and misconceptions, as well as a limited awareness of engagement activities and initiatives.

IMPLICATIONS

Our analysis suggests that the issue of public trust continues to pose a significant challenge to police, in terms of both their understanding of it and the success of engagement activities. Nevertheless, the mental model approach provides a number of insights into the issues that the public expect to be addressed in order to improve trust. Further analysis will help to systematise the trustee attributes that are important to the public and generate a list of guidelines for improving trust. Furthermore, the framework can be used to inform the design of questions targeting key attributes, which can then be incorporated into a survey that will more effectively measure public trust.
SMALL AREA ESTIMATION OF PUBLIC CONFIDENCE

KEY POINTS

Aims To estimate and predict public confidence in the police at the neighbourhood level.

Methods A spatio-temporal interaction Bayesian hierarchical model was developed to model public confidence trends in space and over time.

Findings Public confidence in policing is autocorrelated in space-time. This autocorrelation can be used to estimate and predict public confidence at the neighbourhood level.

BACKGROUND

Public confidence in the police is a state in which the public regard the police as competent and capable of fulfilling their roles. This results from the police being effective in dealing with crime and anti-social behaviour, as well as fair treatment of and engagement with the community. The British model of policing is underpinned by a philosophy of “policing by consent” whereby the police are empowered by the common consent of the public. The public observe the law as a result of their approval, respect and affection for the police rather than compliance being motivated by fear. In this context, public confidence in the police is a key component of effective policing. Persons who are confident in the police are more likely to be cooperative, compliant and crucially to supply the tips which inform proactive policing operations.

MOTIVATION

The Metropolitan Police Public Attitudes Survey (PAS) collects data on the experiences and perceptions of Londoners with respect to crime, policing and anti-social behaviour. While the most robust survey of its kind in the world, the PAS is not designed for use at the neighbourhood level. Improvements are required to support the neighbourhood level policing initiatives which are central to improving public confidence. Public confidence in the police varies across geographical space and over time (see Figure 1). Understanding these patterns at the local level is an important step in developing a targeted confidence intervention strategy.

Figure 1: Group of maps of measured public confidence levels in London for the period April 2012-March 2013. Dark blue areas indicate confidence levels above the London-wide average.

Legend

- River Thames
- Confidence above MPS average
- Confidence below MPS average

Quarter 29

Quarter 30

Quarter 31

Quarter 32
SMALL AREA ESTIMATION

A spatiotemporal Bayesian hierarchical modelling approach enabled the estimation and prediction of public confidence in the police at the small area level. This approach allows trends to be explored in space-time and neighbourhood level intelligence to be obtained from sparse sample survey data.

RESULTS

Public confidence was found to exhibit spatiotemporal dependence. In Figure 2, we show a space-time variogram, which illustrates the strength of the dependence in space and time. Neighbourhoods up to 1 kilometre away in space and two quarters away in time are correlated. A Bayesian hierarchical model was then developed which allowed public confidence levels to vary by neighbourhood and temporal quarter. It also includes spatial, temporal and spatiotemporal components, and was used to estimate and predict public confidence levels at the neighbourhood level (see Figure 3).

IMPLICATIONS

This research contributes evidence of the autocorrelation of public confidence in space and time. This autocorrelation was leveraged in a spatiotemporal model to produce estimates and predictions at a level which can be useful in enabling officers to design targeted strategies to improve public confidence. The estimates and predictions obtained can better enable officers to prepare for the proactive public confidence interventions required to meet the concerns of the local community. This approach also allows hot spots and cold spots of public confidence to be better identified and examined.

Figure 2: 3D representation of a space-time variogram which describes the space-time structure of public confidence

Figure 3: Group of maps of estimated and predicted public confidence levels in London for the period April 2012 - March 2013. Dark blue area indicate confidence levels above the London-wide average.
It has been acknowledged for some time now that the relationship between the police and the rest of society is an important factor in the prevention of crime. Evidence suggests that the public’s confidence in the police affects, among other things, the willingness of citizens to obey the law and cooperate with officers, and is therefore a crucial issue for police legitimacy. In addition to this, recent years have seen an increasing recognition that perception of the police is an important aspect of public wellbeing, with the result that increasing confidence is seen as an end in itself. Because of this, many forces have set explicit targets for the improvement of public confidence; the MPS, for example, has been required to achieve a 20% improvement between 2013 and 2016.

In seeking to improve public confidence, it is natural that the police should seek to tailor their efforts to particular sections of the population, by focusing on groups with particularly low confidence, for example, or by addressing specific concerns amongst others. This is extremely challenging, however: the relationships between confidence and socio-demographic indicators are subject to complex interactions, making generalisation difficult. Furthermore, aggregate-level relationships are of limited use in informing strategies for confidence improvement: it is far from clear how the concerns of a particular age group can be addressed at a city-wide level, for example.

One way in which the influence of multiple socio-demographic factors can be brought together is through the use of geodemographics. Geodemographics is “the analysis of people by where they live” and is used to identify socially similar groups on the basis that similar people are more likely to live within the same locality, have similar lifestyles, and share similar views. Using this approach, populations can be grouped according to their various characteristics, providing an overview of any particular neighbourhood which can be used to make inferences about the individuals within it. This is of clear value for policing, since it provides a means to assess how the combination of measured factors influences public attitudes. If areas can be profiled in these terms, then efforts to improve public confidence can be tailored spatially, according to the needs of particular neighbourhoods.
A number of geodemographic classifications are available in the UK, including one which is specific to London and was developed by our research team: the 2011 London Output Area Classification (LOAC; see Figure 1). Using this as a basis, we examined spatial and temporal trends in the public perception of the MPS, as measured by the Public Attitude Survey (PAS). This is a monthly cross-sectional survey designed to elicit the public’s perceptions of policing needs, priorities and experiences, with a number of questions specifically focussed on issues of public confidence.

**GROUP-LEVEL TRENDS**

Our results show that substantial differences can be observed between LOAC supergroups in terms of their attitudes towards the police. In Figures 2 and 3, we show the trends over time in the responses to 5 key questions for 2 distinct geodemographic groups: ‘urban elites’ and ‘multi-ethnic suburbs’. This is significant because it implies that these groups do indeed display idiosyncratic characteristics with respect to their perception of police. Knowledge of an area’s classification therefore allows inferences to be made about the level of confidence of people living there.

**IMPLICATIONS FOR POLICING**

The use of geodemographics has the potential to significantly improve the precision with which police efforts to improve public confidence can be focussed. The fact that spatiotemporal variation can be explained in these terms suggests that classification systems such as the LOAC provide a simple and convenient basis on which to target initiatives. Since each classification corresponds to a stylised socio-demographic ‘portrait’ of the kind of person who lives there, interventions can additionally be designed in ways which are tailored to the needs of particular groups.

Figure 1: The 2011 London Output Area Classification, with areas coloured according to geodemographic supergroups.

Figure 2: Trends in PAS responses for the LOAC supergroup ‘urban elites’.

Figure 3: Trends in PAS responses for the LOAC supergroup ‘multi-ethnic suburbs’.
The CPC project has at its core a strong practical focus, and an essential component of the project is therefore the translation of research into real-world tools. We have developed a number of our research outputs into stand-alone tools suitable for use by practitioners. These perform a number of tasks, including both predictive policing and performance evaluation functions. They are designed with police end-users in mind, and act as prototypes for the eventual large-scale deployment of these systems in real-world police forces. They are integrated together in a suite of tools, which provides a unified system for data-driven policing support.

**PREDICTIVE MAPPING**

On the basis of our research into crime prediction, we have developed a predictive tool which can be used to prospectively identify the locations of future crimes in a real-world setting. The tool implements our network-based predictive algorithm, as described in *Prediction on street networks*, which we found to offer significant improvements in predictive performance when compared with other algorithms currently available.

The tool takes recorded crime data as its input, and applies a learning algorithm to determine the optimal parameters for crime prediction. These can then be applied to identify the streets at greatest risk at future times – typically one day ahead – for a range of crimes. The tool produces maps which display the highest risk streets against a map of the area, which can be provided to officers or used in operational briefings. As well as providing higher accuracy, the identification of streets allows patrol activity to be pinpointed to the locations at greatest risk.
**MAP-MATCHING**

Any analysis of police behaviour relies crucially on knowing exactly where officers have travelled. Although GPS technology facilitates this to an extent, reconstructing paths through the network is far from straightforward: GPS readings are subject to errors, and low sampling rates mean that interpolating between signals can be problematic. To address this, we have developed an algorithm for this ‘map-matching’ task which is packaged as a generically-available tool.

Given any GPS tracking data as its input, our tool infers the most likely route through the network, adjusting for reading errors and characteristics of the streets involved. It does this probabilistically, so that the likelihood that the inferred route is correct can be quantified. The tool can be applied in policing to produce detailed movement logs, and also has potential application in other transport-related settings.

**SUPPLY AND DEMAND**

The geospatial processing techniques we have developed can be applied to police GPS data to infer exactly which routes through the street network have been taken by officers in the course of patrol. This provides a complete record of police activity, and can be taken as a measure of how the ‘supply’ of policing – in the sense of its visual presence – is distributed. By comparing this to the distribution of ‘demand’, such as calls for service, the extent to which supply and demand are aligned can be explored.

We have produced a tool which allows this alignment to be visualised and quantified. The tool reads live tracking data collected by the police, and – for any analysis period chosen by the user – shows which areas and streets have received levels of patrol that are disproportionate to the volume of incidents occurring there. This can be used as a decision support tool for commanding officers in identifying areas which may be either under- or over-policed.
PATROL ROUTING

As described in *Routing strategies for police patrol*, our research has sought to address the issue of patrol routing in policing: a critical problem in the translation from data-driven insight into operational procedure. We have implemented the dynamic patrol routing strategy we developed as a tool which can be used in real-world policing environments to support efficient officer tasking.

The tool suggests efficient strategies for the patrolling of specified hotspots, such as those identified by our predictive tool. The algorithm can be tuned to particular operational settings – with officer numbers specified, for example – and accounts for the configuration of the local street network. By integrating this with existing deployment systems, officer tasking can be supported in an evidence-based way.

BEHAVIOUR AND ACTIVITY ANALYSIS

We have implemented our framework for the identification of activity groups from individual GPS traces as a tool that can be used to analyse the behaviour and activity patterns of foot patrol officers. This is of use for both performance evaluation and for identifying aspects of behaviour which could be improved.

The tool can visualise high-volume GPS traces in space and time, identify the places and time periods of high patrol intensity, as well as grouping officers who share similar patterns. It can also provide summaries of the time spent on different activities by different type of police officers. This can be used as a data-driven component of performance evaluation in an operational policing context.
The path to the following policy responses leads from the research questions and analytics that have been developed throughout the CPC project. Each requires innovation in the creation, maintenance and analysis of data resources that are already a by-product of routine policing activities. In some instances the policy responses also require linkage of data arising out of policing in environments that are secure, while other responses also entail the supplementation or even partial replacement of conventional survey procedures with other instruments to monitor the ways in which reassurance policing is received.

**POLICY GOAL: IMPROVE PUBLIC CONFIDENCE IN POLICING**

Public confidence in policing is most obviously shaped by the likelihood of being a victim of crime, but depends also on the visibility of policing, the victim experience, and the ways in which the social and human capital in our communities can be harnessed in partnership activities. Confidence is fundamentally built upon trust, and the CPC project has identified significant gaps in trust between and among the stakeholders in both communities. The issues that matter most to the public are perceived differently by experts, and limited awareness of engagement activities and initiatives have been revealed by the public during our interviews.

**Recommendations:**

1) Work needs to be done on both sides to increase the public’s understanding of police work and foster better relationships, through better communication and greater community engagement.

2) This requires re-thinking the design and implementation of public attitude surveys to better reflect the activity patterns of citizens (since public confidence is not shaped exclusively in the residential setting) as well as the activities of police officers. The current public attitude survey conducted by MOPAC should be fully reviewed in order to accommodate events such as ‘signal crimes’. The new design should remain representative of the population that the MPS serves, but should better reflect the accountability of individual Borough police forces.

3) Redesigned public attitude surveys should be augmented with the conscientious use of social media sources, carefully reweighted to ensure that the attitudes and views of non-users are appropriately represented.

4) The small area estimation and analysis of public confidence with geodemographics show that public confidence interventions should be targeted locally and in a way that is specific to geodemographic types.

**Policy priority:** This requires reappraisal of existing survey instruments, development of new ones, and greater efforts to explain methods and achieve ‘buy in’ from front line officers. The new tools and data resources should be free to use as part of the Open Data movement that is shaping similar initiatives in other areas of public service delivery.

**POLICY GOAL: REDUCE COSTS AND IMPROVE EFFICIENCY (“DO MORE FOR LESS”)**

Borough commanders are constantly updating their strategies to improve operational efficiency under intense resource constraints. In addition to that concerning crime occurrence, data on officer activity patterns can provide valuable feedback and evaluation of performance, which should be considered with higher weight in their decision-making. To facilitate this, simple tools to help officers understand the issues are required.

**Recommendations:**

1) Further development of the CPC strategic planning tools will give the commanding officers of individual police forces a clear picture of how routine activities function and how emergencies can be coped with. The same tools will also be of use in making budgetary or procurement decisions.

2) Tools for the analysis of supply and demand will identify where scarce resources in patrolling might be more effectively redeployed, and to achieve more efficient deployments of officers between neighbourhoods, over time.
3) Behaviour and activity analysis tools will offer insight into the micro-level behaviour of police officers during routine patrol, which might be used to identify innovative (but undocumented) front line practices that might be more widely adopted. Conversely, less effective activities could be phased out over time.

**Policy priority:** The prototype tools developed in CPC need to be completed and implemented as viable operational products so that they can be widely adopted.

**POLICY GOAL: CRIME REDUCTION AND PREVENTION**

Coarse grid-based heatmaps are currently used to guide frontline officers to predicted high risk areas, but the grid frames are neither intuitive nor appropriate for patrols conducted along street segments. Partly as a consequence, many officers have reservations about their utility, and are reluctant to use them. Even when officers are open to using predictive maps, they are difficult to use in operational situations.

**Recommendations:**

1) The results of the CPC research provide road network-based crime predictions for different crime types at the street segment level, which can be used to guide police officers to the right place at right time for crime prevention. The power of the predictive approach can be evaluated using empirically-based accuracy evaluation measures.

2) Integration of our patrolling tool within an online central control system has the potential to provide guidance to frontline officers in selecting areas and routes to patrol, thereby complementing and supporting existing policing procedures. Its use in this way can contribute to the improvement of the efficiency of routine patrolling, while also making operational practice more resilient to emergency situations.

**Policy priority:** Frontline officers should be encouraged to accept the concept of intelligent patrol, and to use the network-based predictive maps to supplement their own experience of where and when it is best to patrol. The system of online patrolling might also be developed so that frontline officers can be guided and coordinated by the control centre in an efficient way, though this will also require fundamental shifts in behaviour and so may form part of a wider initiative.

**IN SUMMARY**

Policing is facing great challenges and opportunities. A fundamental paradigm shift is required to capitalise upon the value of Big Data for intelligent policing. Intelligence is not only about prediction, but also how to act on it, and how to evaluate the action. This requires behaviour change from senior and frontline officers alike in order to use the insights that can be gained from police data, as part of wider adoption of evidence-based policing. Adoption of the tools developed here requires training, but also a greater openness to the core organising concepts of predictive policing. We believe that the policy implications specifically set out here will benefit digital policing, not only in London, but in other large cities across the UK and beyond.


SpaceTimeLab is a multi-disciplinary research centre at UCL Department of Civil, Environmental and Geomatic Engineering. It brings together researchers from a diverse set of fields, in geomatics, GIScience, geography, computer science, crime science, mathematics, social science, and transport.

SpaceTimeLab’s mission is to generate actionable insights from geo-located and time-stamped data for government, business and society. Using integrated space-time thinking, we develop theories, methods and platforms for prediction, profiling, visualisation and simulation.

Our current project portfolio covers four key themes:
1. Transport and Mobility
2. Security and Policing
3. Business Intelligence
4. Environmental Resilience

We are also developing applications in the following areas with new partners:
5. Health
6. Economics

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