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Introduction to crime forecasting

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Abstract

This short paper introduces the six papers comprising the Special Section on Crime Forecasting. A longer title for the section could have been ''Forecasting crime for policy and planning decisions and in support of tactical deployment of police resources.'' Crime forecasting for police is relatively new. It has been made relevant by recent criminological theories, made possible by recent information technologies including geographic information systems (GIS), and made desirable because of innovative crime management practices. While focused primarily on the police component of the criminal justice system, the six papers provide a wide range of forecasting settings and models including UK and US jurisdictions, long- and short-term horizons, univariate and multivariate methods, and fixed boundary versus ad hoc spatial cluster areal units for the space and time series data. Furthermore, the papers include several innovations for forecast models, with many driven by unique features of the problem area and data.

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1. Why crime forecasting is new

Crime forecasting is not widely practiced by police. While there are numerous econometric studies of crime or incorporating crime in the literature, one is hard-pressed to find police departments or other police organizations making regular use of forecasting—econometric or extrapolative—for deployment of limited resources. There are several explanations, but mainly we think that crime forecasting was simply thought not to be useful or feasible until recently.

The major target of police tactics had been persons and their criminality; for example, analyzing the modus operandi of serial criminals, and apprehending them. Of course, conventional forecasting methods are of little use in predicting the behavior of individual serial criminals.[1] Crime forecasting, using methods such as those studied in this journal, did not become relevant until two things occurred. First, the *criminality of places* was established based on theories such as routine activities (Cohen & Felson, 1979), the ecology of crime (e.g., Brantingham & Brantingham, 1984), and hot spots (spatial clusters of crime) (Sherman, Gartin, & Buerger, 1989). Second, within the past 5–10 years, police began regularly

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[1]Instead geographic profiling has emerged as a method for predicting the whereabouts of serial criminals; e.g., Rossmo (1999). Rule-based expert systems and data mining are additional methodologies potentially useful for identifying crime series.

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mapping crimes using geographic information systems (GIS). The targets are still criminals, but the focus of crime prevention and law enforcement is on places where crime tends to take place. The data are frequency counts of crimes by time period and geographic area, and these data are potentially forecastable.

But is accurate crime forecasting possible? There is a great deal of uniqueness and randomness associated with crime. Nevertheless, there are patterns. Most influential in establishing this fact are the recent opportunity theories of crime, especially the routine activities theory attributed to Marcus Felson (Cohen & Felson, 1979), who has a paper in this special section and whose theory is applied in several other papers in this section.

One of the reasons that crime forecasting may have been judged to be infeasible in the past is that the desired scale for observation is too small for reliable model estimation. For tactical purposes, police must pinpoint crime in areas as small as possible, at the patrol district level (geographic area of one officer or team) or smaller. We know that forecast errors increase as data aggregations become smaller, but unfortunately, there has been very little systematic study of the effects of data scale on forecast accuracy. Other areas, such as sample survey design, have had scale issues as a major research topics (e.g., the small area statistics problem as in Platek, Rao, Sarndal, & Singh, 1987). The small literature on data pooling in forecasting is a step toward remedying forecasting scale problems (e.g., Bunn & Vassilopoulos, 1999; Duncan, Gorr, & Szczypula, 2001). Felson and Poulsen (2003) and Gorr, Olligschlaeger, and Thompson (2003) address the scale issue for crime forecasting in this special section.

2. The origins of crime forecasting

After the major successes of crime mapping by police in the 1990s, in 1998 the US National Institute of Justice (NIJ) awarded five grants to study crime forecasting for police use as an extension of crime mapping.[2] Instead of only mapping recent crimes and assuming that observed patterns would persist, the objective was to forecast crime one period ahead, with results displayed as maps. With accurate short-term crime forecasts, police would be able to take tactical actions such as targeting patrols to hot spots, conducting surveillance for deployment of special units (e.g., crackdowns for drug enforcement), scheduling vacations and training to trough crime months, making crime alerts available to neighborhood watch groups, etc. Two papers in this Special Section are results of those grants, Gorr et al. (2003) and Liu and Brown (2003).

At about the same time, the UK's Home Office published among the first crime forecasts for police planning and crime reduction policy (Dhiri, Brand, Harries, & Price, 1999). At this level, government and police can engage in an informed dialog about priorities, allowing police to plan budget requests for additional resources, redeploy manpower across precincts to balance workloads, shift resources between prevention and enforcement activities, etc. The papers by Harries (2003) and Deadman (2003) provide a postmortem on the Dhiri et al. (1999) forecasts.

In the United States, GIS and other information technologies have enabled a management-by-objectives approach to policing that has been widely implemented in the form of monthly Compstat meetings (e.g., McDonald, 2002). Precinct commanders review recent performance via tabular and map displays in widely attended meetings, and outline short-term plans. Key to success are objective performance measures, including crime levels, and peer pressure. Compstat provides for accountability of police as well as problem solving with key decision makers present. In the New York Police Department, where CompStat originated in 1997, these meetings focus on both serial criminals and hot spots. Compstat or similar meetings will be prime consumers of short-term crime forecasting technologies, when they become available to police.

3. The papers in this special section

The purpose of police crime forecasts is to directly support crime prevention and law enforcement. Other parts of the criminal justice system have different forecasting needs, but those needs are not addressed here (e.g., corrections facility planning of

[2] Olligschaleger (1998) was influential in directing the NIJ's attention to crime forecasting.

prison capacity based on demographics, predicting impacts of proposed changes in judicial sentencing policies using input/output models, predicting recidivism for prisoner release to parole based on prisoner profiles, etc.).

The papers by Harries (2003) and Deadman (2003) confront forecasting a national crime series that seems to have deviated from a long-term trend. Harries and his Home Office colleagues (Dhiri et al., 1999) made a 3-year forecast of residential burglaries for England and Wales, using a cointegrated econometric model that returned experienced sharp declines to the long-term growth trend. Deadman compares alternative forecast models for the same forecast series and horizon. Both papers' forecasts were made ex ante, and now that time has past, the papers include a postmortem on the forecasts. Important policy considerations arise from this work. One is that the effect of police actions was not included in any of the forecast models, but unlike sales forecasting where competing firms cannot influence demand, police are more like monopolists who can influence crime levels. Hence, if police policies and efforts are successful in response to a forecasted crime increase, they will destroy the accuracy of the forecast. Did that happen in this case? What is success? Should the forecasts have been intended to ‘‘motivate the sales force’’? Should policy analysts use multiple perspectives and forecast models instead of a single model?

The remaining four papers provide methods for short-term, tactical decision making at the sub-jurisdiction level, but break further into two subcategories. Felson and Poulson (2003) and Gorr et al. (2003) use data for fixed geographic observation units (cities and police precincts, respectively), whereas Corcoran, Wilson, and Ware (2003) and Liu and Brown (2003) work with ad hoc areas for spatial clusters of crimes (i.e., hot spots). Forecast methods for fixed geographic units can easily draw on traditional time series methods for forecasting, plus make good use of cross-sectional data using spatial econometric methods such as models with spatial lags (Anselin, 1988) and data pooling methods (e.g., Bunn & Vassilopoulos, 1999; Duncan et al., 2001). In contrast, the hot spot methods have the unique feature that they include identification of spatial clusters and their ad hoc boundaries as well as forecasting.

Forecast methods for fixed boundary and ad hoc spatial cluster areas are complementary, with the fixed boundary forecasts narrowing the search for problem areas, and clustering methods then diagnosing and focusing in on specific targets. Gorr et al. (2003) provide evidence, from a fixed-effects panel data model for explaining forecast errors, that the predominant factor influencing short-term crime forecast accuracy is geographic scale. Forecast absolute percentage errors are primarily a function of the inverse of average crime count in an historical crime series. The average crime count must be at least 25–35 per month before forecast MAPEs decrease to the order of 20 percent. In moderately large cities in the eastern United States, this translates roughly to geographic areas about 10 city blocks on a side in high crime areas. While these areas are too large to direct patrols to targets, etc., they are small enough to narrow attention (e.g., Pittsburgh, PA has 105 square grid cells approximately 10 blocks on a side). With attention drawn to a few such areas forecasted to have large crime increases, crime analysts can then apply hot spot methods within those areas for detailed forecasting and targeting.

Felson and Poulsen (2003) also address the scale problem of crime forecasting. In particular, they examine city-to-city variation in hour-of-day seasonality for robberies. To conserve degrees of freedom, they propose that forecasters use three order statistics (median and two quartiles) and further derived quantities based on a definition of 5:00 AM as the start of a crime day.

Liu and Brown (2003) provide one of the first applications of point-pattern methods of geography to forecasting. They model a transition density for the risk of crime across a police jurisdiction based on experienced preferences of criminals for locations. As such, their model is an extension of the widespread police practice of assuming that a crime spatial cluster will simply persist. In a demonstration of methods, the authors provide evidence that their model outperforms police practice.

Corcoran et al. (2003) also identify crime clusters, but then create relatively long historical time series for resulting ad hoc boundaries. As a result, they apply traditional time series methods including a naïve method, a regression model, and a neural network. Their work uses the novel and indeed remarkable Gamma Test (e.g., Evans & Jones, 2002) which estimates the error term MSE for a best, but unknown, smooth-function forecast model. This information plays a central role in specifying the regression and neural network models. Empirical evidence suggests that the neural network model performs best for nonchaotic time series.

4. Summary

The six articles of the crime forecasting section cover a wide and representative range of topics in this new application area. Included are long-term forecast models for planning and policy applications as well as short-term forecast methods for tactical decision making. On the methodological side, models and methods include exponential smoothing methods, Box Jenkins ARIMA multivariate transfer models, neural networks, and cointegrated econometric models. Innovative aspects of these models and papers include application of the Gamma Test for neural network modeling, application of a Gini-index-based measure for relating independent variables to crime spatial clusters, construction and validation of point-pattern transition density models for space and time forecasting, design of seasonality measures for data aggregation, and systematic study of the effects of data aggregation level (geographic scale) on forecast accuracy.

There of course remains much to be done in crime forecasting. Crime space and time series data are becoming available for researchers interested in the area. In the United States, the National Archive of Criminal Justice Data is one such resource (see http://www.icpsr.umich.edu/NACJD/nij.html).

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