Mapping the Unequal Risk of Police Violence: A Critical Response to Predictive Policing

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Introducing the Police Violence Risk Map

Law enforcement agencies across the US are increasingly using predictive software programs to identify high-crime areas and likely locations for future crime. Critical scholars across disciplines argue that predictive crime mapping is inherently biased: Prediction relies upon the past to create a vision of the future, and because US law enforcement has long been biased against people of color, predicted futures based on past crime data carries forward such bias (Mayson, 2019).

There is a certain risk that any person in the US could suffer violence or death at the hands of law enforcement. Yet such risk is disproportionately higher for persons of color, especially black men (Edwards, Lee, & Esposito, 2019). In a county-level study of police shootings across the US, Ross (2015) finds the probability of being black, unarmed, and shot by police to be 3.49 times higher than the probability of being white, unarmed, and shot by police. These rates vary spatially (Schwartz & Jahn, 2020). Ross (2015) finds that counties associated with greater metropolitan populations, a large percentage of low-income black residents, and greater income disparity hold a disproportionate risk to black persons of being shot by the police.

Police violence, thus, is a spatially heterogeneous phenomenon, and the disparities of this risk can be modeled to estimate the relative risk over space. This project – the Police Violence Risk Map – flips predictive crime mapping on its head by creating just such a risk map for the City of New York (NYC). It assesses the disparate risk that residents of different races and ethnicities suffer of being killed by the New York Police Department (NYPD) and publicly shares the resulting risk maps in an interactive mapping interface. This project thus joins the growing research literature on predictive policing, and it does so from a critical GIS perspective.

Critical GIS encompasses two main lines of work: critique of mainstream GIS technologies, ontologies, methods, and impacts, and second, the active employment of the technologies on community-based projects or projects that otherwise push back on conventional GIS use (Wilson, 2017). For example, "counter-maps" offer a perspective on space that differ from traditional views. These might use new data, such as community-created data and volunteered geographic information (VGI), or a focus on different subjects than conventional maps (see, e.g., Native Land Digital, 2015).

The Police Violence Risk Map builds from both strands of the critical GIS literature, as it critiques the use of spatial technologies in predictive policing whilst offering a vision of cityspace, based on community-created data, that pushes back on the one envisioned by predictive crime maps. It is a counter map, showing the dangers wreaked by law enforcement across cityspace, rather than the dangers of crime that we are more used to seeing. It will offer the (unneeded) sheen of objectivity to the greater feelings of risk felt by black residents, in the same way that predictive crime algorithms cloak biased policing with a veneer of objectivity.

Our project is well suited to this year's AutoCarto themes. It highlights the lack of data integrity that predictive policing is based upon. It is inclusive in that it is based upon VGI, will be shared publicly online, and will seek to engage community feedback. The project speaks to empathy as it is inspired by the disparate danger that different people experience across US cities at the hands of police.

Predictive Policing: Biased Data and Biased Patrols

The use of place-based predictive policing works in conjunction with two other broader systemic factors. First is the ever-increasing number of low-level offenses that governments add to their criminal codes, a phenomenon referred to as "overcriminalization" (Luna, 2005) or "mass criminalization" (Carbado, 2016). Enforcement of low-level infractions such traffic violations is highly discretionary, and officers are more likely to engage with people of color for minor infractions and more likely to cite or arrest them for violations (Slocum, Huebner, Greene, & Rosenfeld, 2020).

The second systemic issue is the nature of the data fed into predictive policing algorithms. Theoretically, a dataset containing all commissions of relevant crimes would yield the most accurate predictions as to future criminal patterns. But, in the language of statistics, such population data of criminal activity does not exist. Instead, police records are but a sample of the broader population of criminal activity. Crime data are records of police activity, not crime occurrence, and are impacted by any biases built into police activity (Selbst, 2017). The result is that predictive systems reinforce existing biases in policing practices (Jefferson, 2018).

Benbouzid (2018) quotes the first LAPD captain to test the PredPol program as saying, "there is no good or bad prediction" (p. 131). To Benbouzid, this reveals a moral standpoint that the predictions have no effect on the near-future – no consequences. On the contrary, negative impacts are rife. The predictions direct where police will patrol, increasing the number of interaction between residents and law enforcement. Increased police attention has negative health outcomes on residents (Sewell & Jefferson, 2016). The mental health of young men declines with repeated police interactions (Geller, Fagan, Tyler, & Link, 2014), and of course, as the number of stops rises, the number of stops that turn violent increases as well (Carbado, 2016). In the mental maps of police officers, predictive crime maps provide the veneer of objective reassurance that the officers belong there. Predictive policing thus contributes to and further solidifies the racialization of space across American cities (Jefferson, 2018).

Data and Methods

Unlike incidents of crime, law enforcement agencies in the US are not required to federally share specific data on incidents of police violence, so there is no official, comprehensive data set on police violence in the US. Official data varies by agency and, when it is publicly shared, it is never as fine-grained as crime incidence data. In the last few years, researchers have created crowdsourced data platforms to fill this knowledge gap. The Fatal Encounters data set is an on-going project to track incidents of fatal police violence in the US from 2000 to the present (Finch et al., 2019). It relies upon volunteers to comb police reports and media descriptions for incidents and record their location and rich attribute data. The spatial data quality of VGI is variable (Girres & Touya, 2010; Moradi, Roche, & Mostafavi, 2022), but Fatal Encounters has higher and more consistent SDQ than a project such as OpenStreetMap, as volunteers are fully vetted by the Fatal Encounters administrators before than are permitted to add data to the project.

The Fatal Encounters data is far more complete, and more detailed, than any official data set of police-related deaths – across the US, and in NYC in particular. The NYPD shares a data layer of police use of force, but such data is aggregated at the precinct level and does not include the location of individual events.

A variety of programs are now available for predictive policing, such as PredPol, HunchLab, and Risk Terrain Modeling, which each employ their own proprietary algorithm. The work herein will employ the maximum entropy model of the Maxent program. This black-box algorithm was developed for species distribution modeling (Phillips, Anderson, & Schapire, 2006), but has been employed in the literature to social phenomenon such as patterns of VGI contributions (Zhang, 2020) and warehouse siting for transportation planning (de Oliveira, de Oliveira, & Nóbrega, 2021).

As to the features fed into the algorithm, PredPol employs only past crime data. Risk Terrain Modeling also includes environmental features, such as locations of liquor stores (Caplan and Kennedy, 2016), and HunchLab adds demographic features into its mix (Degeling & Brendt, 2018). Our feature selection is inspired by Carbado (2016), who proposes a model to explain the high proportion of black deaths at the hands of police that is based on urban policies and policing strategies that lead to higher levels of interactions between black people and police. These include broken-windows policing, mass criminalization, racial segregation, and the presence of vulnerable populations, such as LGBTQ and poor black women. We also employ features that are likely to be used in predictive policing because, as Carbado (2016) notes, higher levels of police presence lead to higher risk of violent interactions with police.

Projected Project Status in November 2022

Our project is currently being developed by gathering and prepping the myriad feature layers to feed into the Maxent program. This involves a fair bit of data wrangling as factors such as locations of stop-and-frisk events, criminal summons for ‘quality of life’ offenses, and misdemeanor arrest records across NYC each number in the millions for the last 15 years.

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