Geo: A Visual Analytics Tool for Spatiotemporal Analysis

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Abstract. *This paper presents Geo[1], a spatiotemporal analysis tool designed to support criminal analysis tasks such as hotspot detection and police patrol route planning. The system addresses the gap between traditional hotspot mapping and actionable patrol deployment by combining three techniques: MSKDE for high-resolution density estimation, SHOC for intuitive temporal comparison of crime hotspots, and HotSee for generating patrol routes along high-risk street segments. Through a real case study on robbery incidents in Vila Sônia, São Paulo, the paper demonstrates how Geo enables analysts to identify spatial and temporal crime patterns, adapt analysis to street networks, and create operational patrol routes. The results highlight Geo's effectiveness in bridging strategic crime mapping and tactical decision-making, with future work aimed at real-time data integration and broader applications in public safety.*

1. Introduction

In recent decades, the growing challenges posed by urban crime [Fórum Brasileiro de Segurança Pública 2024] have led law enforcement agencies to adopt increasingly sophisticated data-driven strategies. Among these, hotspot policing stands out as an effective approach that focuses police efforts on areas with high crime concentrations [Boba Santos 2012, Chainey 2021]. A key enabler of this strategy is crime mapping, especially through techniques such as Kernel Density Estimation (KDE), which visualizes spatial crime patterns and highlights areas requiring intervention [Eck et al. 2005, Chainey et al. 2008, Hart and Zandbergen 2014].

Despite KDE's widespread use, traditional implementations, typically based on tools like ArcGIS and QGIS, often lack the interactivity needed for operational decision-making. To address this, recent advances have introduced methods such as Marching Squares Kernel Density Estimation (MSKDE) [de Queiroz Neto et al. 2016], which blends KDE with the Marching Squares algorithm to produce smooth, high-resolution hotspot contours. Complementing this, the SHOC (one-SHOt Comparison Tool) technique [de Queiroz Neto et al. 2020] enables intuitive visual comparisons of crime scenarios using logical set operations, even for users without deep technical knowledge.

[1]**Link to the presentation:** `https://youtu.be/u2UvyVvfLNs`

Yet a critical challenge remains: turning spatial hotspot insights into actionable patrol plans. The HotSee algorithm [Nunes et al. 2021, Nunes Junior et al. 2025] addresses this by heuristically generating foot patrol routes through high-crime areas. Unlike conventional pathfinding methods, HotSee prioritizes 'hot segments'—street segments with elevated crime—while considering constraints like route length and operational feasibility. Validated by domain experts, HotSee has shown promising practical results [Chainey et al. 2021].

In this context, we propose GEO, a web-based system focused on simplicity, which integrates MSKDE, SHOC, and HotSee into an interactive visual analytics platform. GEO is intuitive and user-friendly, lowering barriers for analysts and officers to perform advanced crime analysis. Together, MSKDE, SHOC, and HotSee form a unified ecosystem for visualizing, analyzing, and acting on spatial crime data. Their integration into the accessible GEO platform empowers law enforcement to move from insight to action with unprecedented speed and precision.

2. The GEO Project

GEO is designed to simplify the gathering, visualization, and analysis of spatiotemporal data while ensuring tenant data isolation and supporting deployment in any country. It operates along two dimensions: data management and analysis creation.

Data Management. The GEO dictionary organizes data into categories such as Points of Interest (POIs), Areas, Municipalities, Data Sources, and other supporting models. POIs, representing events or objects on Earth, are a core data type, defined by location, type, optional timestamp, and attributes for filtering, visualization, and analysis. Areas are spatial geometries for filtering and choropleth maps. Municipalities function similarly but also enable road network usage for statistical views and graph algorithms. Data Sources support streamlined data import and provenance tracking. Most data, including POIs and geometries, can be uploaded through the interface or via API. GEO also provides built-in datasets like municipalities and road networks during country setup.

To ensure proper isolation of POIs, geometries, and analyses, GEO introduces the concept of *agency*. Each agency encapsulates its own POIs, shapes, and analyses, while shared datasets (e.g., municipalities, road networks) remain globally accessible. Users may belong to multiple agencies but can access only one at a time, allowing GEO to scale securely across clients.

Analysis. A GEO analysis consists of an ordered list of layers, each with visual components displayed over a base map. Users first define a POI filter—by type, time frame, and spatial bounds—then configure algorithm-specific parameters for the selected layer type. Once configured, the layer is rendered on the map, enabling interactive refinement. Each layer supports tailored interactions, such as viewing POI details and street views, displaying statistics for selected areas, or animating route visualizations with road lists. An analysis may also incorporate textual and visual annotations, either attached to specific components or directly to the base map, facilitating the documentation of findings and the construction of a knowledge base. Users can share their analyses with collaborators or make them publicly accessible within their agency.

3. Domain Tasks

To ensure our system addresses real-world needs in crime analysis and policing, we collaborated with public safety professionals and crime analysts in Brazil, the USA, and the UK. Through semi-structured interviews, feedback sessions, and task analysis with officers, analysts, and decision-makers, we identified four key domain tasks that guided the development and evaluation of our visual and algorithmic components. These tasks reflect core workflows in intelligence-led policing and hotspot-focused interventions.

Each domain task (DT) captures a distinct yet interrelated cognitive goal in the crime analysis pipeline, from identifying where crime clusters to determining optimal officer deployment. Together, they cover traditional spatial analysis and operational planning over the street network, supporting both strategic and tactical decision-making.

DT1 - Hotspot Identification in Space. This task involves detecting geographic regions with concentrated crime, typically using point-based incident data. These hotspots inform strategic decisions by highlighting high-crime areas.

DT2 - Hotspot Evolution in Space. Understanding temporal changes in hotspots is essential for retrospective and predictive analysis. DT2 compares hotspots across time windows, times of day, or crime types to detect emerging, shrinking, or shifting areas. This supports evaluating interventions and refining strategies.

DT3 - Hotspot Identification in the Street Network. Unlike surface-based approaches, this task maps crimes to street segments, identifying hotspots as sequences of segments with high intensity. This network-based view aligns with how police operate and is more actionable for planning patrols.

DT4 - Creation of Patrol Routes Based on Street Network Hotspots. Building on DT3, this task focuses on designing efficient patrol routes through high-crime segments. Routes aim to maximize coverage while respecting constraints like patrol time and feasibility, supporting targeted, proactive deployment.

4. Case Study: Applying the Domain Tasks for robbery crimes in Vila Sônia, a Neighborhood of São Paulo

To demonstrate the practical application of our system and the four domain tasks, we conducted a case study on robbery in Vila Sônia, a neighborhood in São Paulo, Brazil. The selected area features a mix of residential, service, and commercial zones and is known for challenges related to robbery and theft.

To enrich the spatial analysis and characterize the area's economic profile, we extracted data from OpenStreetMap on the number of commercial, residential, and service establishments within the studied geometries. These counts support classification based on economic composition. As of 2025, Vila Sônia includes approximately 70 commercial, 195 service, and 260 residential elements—525 features in total—highlighting its predominantly residential and service-oriented nature.

The case study employed multiple analytical components: the MSKDE algorithm for density estimation, the SHOC method for comparative hotspot analysis, and the HotSee route generator for tactical planning. While we omit detailed explanations of algorithm parameters due to space constraints, their behavior and configuration are fully described in the original publications.

DT1. We began by analyzing geolocated crime incident data for the neighborhood over one year. We generated a surface-based hotspot map using MSKDE with empirically defined parameters (a bandwidth of 800 meters and a threshold of 30%). The results highlighted two primary areas of high crime concentration. Figure 1 shows the representation of the DT1.

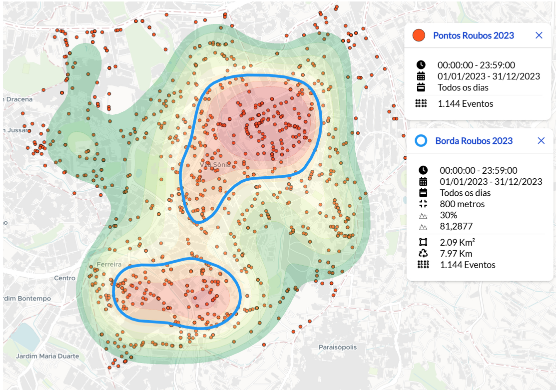

Figure 1. The image displays red dots representing robbery incidents and two blue polygons outlining hotspot areas. The background is shaded in green, yellow, and red to indicate regions with increasing levels of crime density.

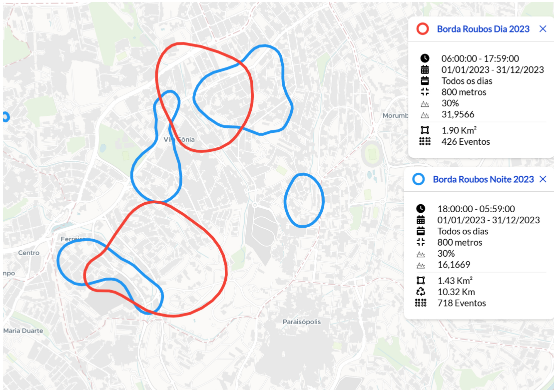

Figure 2. The image presents hotspot areas for robbery incidents in 2023. Red polygons represent high-density areas during daytime hours, while blue polygons correspond to nighttime hotspots.

DT2. To investigate temporal dynamics, we divided the data into day and night periods and repeated the MSKDE analysis. Using SHOC's set-operations-based comparison view, we visually analyzed the changes. Figure 2 shows the representation of the DT2, while table 1 shows the economic profiles of the areas, collected from the OpenStreetMap Project. The change in robbery hotspot areas from day to night can be explained by how people use the city at different times. During the day, crimes happen more in places with many shops and services, with more people and more chances to steal valuable items. These places become quiet at night, and robberies move to residential areas. In these areas, people may be walking alone or arriving home, and the streets are usually darker and less busy, making it easier for criminals to act.

Area Name	Commercial	Services	Residential
Daytime Robbery Border 2023	10	36	3
Nighttime Robbery Border 2023	4	23	9

Table 1. Number of commercial, service, and residential establishments by time of day within the hotspot borders (2023).

DT3. Next, we mapped the same robbery incidents onto the street network and calculated crime frequency per segment. Applying a 50% cumulative crime threshold, we identified the top high-risk segments, which largely align with the surface-based hotspots but offer more detailed, actionable insights. Notably, several high-crime segments cluster around the public transport station, at the center of the hotspot polygon, revealing how secondary streets contribute to criminal movement between hotspot zones. Figure 3 shows this visual component.

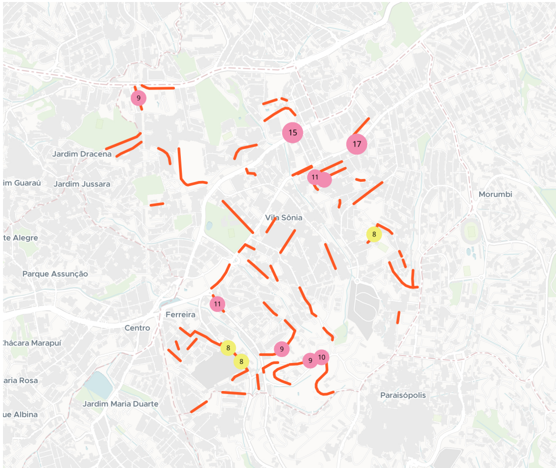

Figure 3. The image presents robbery hotspots in 2023 based on the street network structure of Vila Sônia. Red segments represent high-crime street segments identified through cumulative frequency analysis. Colored circles indicate a high number of robberies.

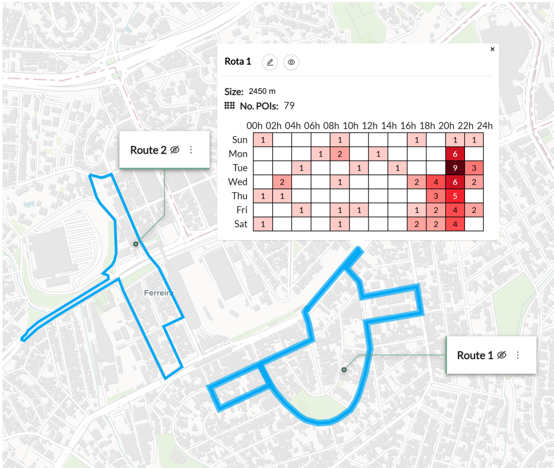

Figure 4. The image shows patrol routes overlaid on the street network. The blue lines represent predefined patrol paths. The table summarizes the frequency of events along Route 1. The route covers a total length of 2450 meters and includes past 79 events.

In the DT3 task, we adapted hotspot detection to Vila Sônia's street network. Rather than using surface density, crimes are assigned to individual segments, with hotspots defined as those with the highest robbery intensity. As illustrated, key segments in Vila Sônia and surrounding areas appear in red, indicating high-crime corridors. Colored markers show incident clusters, with the count per segment. This network-aware approach reflects how officers operate and supports targeted deployment to high-risk streets.

DT4. Finally, using the HotSee algorithm, we generated patrol routes that cover the identified hot segments while satisfying operational constraints (routes between 1000 and 2500 meters and circular paths). Two routes were requested and successfully generated, both in the northeastern section of Vila Sônia near the bus station, the robbery hotspot core. GEO lets users specify patrol mode—on foot, bicycle, or vehicle—ensuring suitability to operational needs. Alongside route maps, the system provides summary tables of incident frequency by day and time. Users may also edit patrol paths manually to integrate field knowledge or correct limitations in OpenStreetMap data. This case study illustrates how our system supports a full analytical workflow for hotspot policing, from spatial analysis to tactical route planning, enabling more targeted, informed crime prevention.

5. Conclusion

This paper presented Geo, a web-based visual analytics platform designed to support law enforcement in analyzing and responding to urban crime through integrated spatiotemporal tools. Combining three key algorithms—MSKDE for hotspot visualization, SHOC for temporal hotspot comparison, and HotSee for generating patrol routes—Geo provides a user-friendly interface for analysts to identify, track, and act upon spatial crime patterns. A case study in Vila Sônia (São Paulo) illustrates the system's ability to support domain tasks such as spatial and temporal hotspot analysis, crime mapping along street networks, and patrol route planning. Future work includes improving the integration of real-time data sources, refining route-generation heuristics for dynamic environments, and expanding usability for broader public safety applications beyond policing.

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