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A Visual Analytics Approach to Facilitate Crime Hotspot Analysis

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Figure 1: *A typical SHOC analysis. Red polygons represent hotspots for robbery in the daytime, whereas blue polygons represent hotspots for robbery in the nighttime. Other visual components: (a) the annotation toolbar, (b) legends, (c) a graphical annotation example, (d) the spatial filter toolbar, (e) the layers control, and (f) a textual annotation example.*

Abstract

Computer-based technology has played a significant role in crime prevention over the past 30 years, especially with the popularization of spatial databases and crime mapping systems. Police departments frequently use hotspot analysis to identify regions that should be a priority in receiving preventive resources. Practitioners and researchers agree that tracking crime over time and identifying its geographic patterns are vital information for planning efficiently. Frequently, police departments have access to systems that are too complicated and excessively technical, leading to modest usage. By working closely together with domain experts from police agencies of two different countries, we identified and characterized five domain tasks inherent to the hotspot analysis problem and developed SHOC, a visualization tool that strives for simplicity and ease of use in helping users to perform all the domain tasks. SHOC is included in a visual analytics system that allows users without technical expertise to annotate, save, and share analyses. We also demonstrate that our system effectively supports the completion of the domain tasks in two different real-world case studies.

CCS Concepts

• ***Human-centered computing*** → ***Visual analytics;*** *Visualization systems and tools;*

1. Introduction

We worked with two police departments in the United States of America and one police department in Brazil in order to identify a set of domain tasks that would have a significant impact on police operations, and to develop a visual analytics solution to address them.

It is well known that geographic location is a prime factor in crime [WEB*16, WGY12]. Therefore, the police usually adopt analytic systems that use spatial hotspot maps to predict crime and to plan patrols. That prediction-and-plan approach aims at developing a more proactive posture and making more rational use of resources [BS12].

Our collaborators from the USA are accustomed to use visual analytics tools that include hotspot analysis. However, the delivered solutions did not fully meet their requirements. Our Brazilian collaborators, on the other hand, routinely use standard Geographic Information Systems (GIS) to create static hotspot maps by applying Kernel Density Estimation (KDE) [Ros56] to a historical data set of Events. Nevertheless, the process of generating and distributing the maps was admittedly inefficient. Usually, a small team of statisticians helps 22 regiments of 500 police officers each to patrol 20 designated areas in the state. Even though some of the regiments have skilled personnel that is capable of using GIS tools, the time they take to produce hotspot analyses is prohibitive.

Practitioners and researchers consider KDE the most prominent technique for generating hotspot maps. They agree that KDE not only is more suitable for crime analysis [BS12] but also outperforms other methods, such as spatial ellipsis and choropleth maps, regarding crime prediction [CTU08].

During the first two years of collaboration, we realized that crime hotspot analysis would benefit from a tool for enabling spatial comparisons. We also recognized that such a tool should be as simple as possible for non-technical users to perform hotspot analysis tasks easily.

To help the police to do those tasks, we developed a visual analytics system –CrimeWatcher that also includes SHOC (one-SHOt Comparison Tool). This tool allows users to quickly make clear spatial comparisons of hotspots characterized in five domain tasks. SHOC applies set-like operations on superimposed geometries to provide interpretable analyses that are ready to be explored, annotated, and shared with others (see Figure 1).

A prototype of the system was evaluated and adopted by the Brazilian Ministry of Justice and Public Safety, through the National Department of Public Safety. The government created a production version of the system, renamed it to "Geo Inteligência" and released it to all Brazilian states to track crime evolution, as part of a national program for combating violent crime, the so-called "Forward, Brazil" program [dJeSP19].

In summary, the main contributions of this paper are the characterization and abstraction of the hotspot analysis problem into five domain tasks and SHOC, a practical tool that facilitates performing the domain tasks by providing a straightforward way of making spatial comparisons, using set-like operations on superimposed geometries for visualization, demonstrating its effectiveness in two different real-world case studies.

The remainder of this paper is organized as follows. In Section 2, we review relevant related work. In Section 3, we characterize the problem of hotspot analysis using analytic tasks, and identify domain experts' requirements. In Section 4, we describe our approach. In Section 5, we present two case studies. In Section 6, we discuss our approach and its limitations. Finally, in Section 7, we draw some conclusions and outline directions for future work.

2. Related Work

In this section, we discuss how GIS and visual analytics systems deal with crime data visualization.

Geographic Information Systems (GIS) [Esr15, Qua17] usually can generate static KDE hotspot maps using historical crime databases. However, since such maps are suitable for the visual inspection of a single situation [BS12], to compare several KDE maps at once is difficult because users cannot overlap them efficiently, due to occlusion. An alternative solution would be to examine maps side by side, but, for that to be somewhat acceptable, systems have to provide a way of synchronizing points of view, colors and densities among maps [CR05]. Unfortunately, those functionalities are not standard in GIS systems and their implementations would require time and advanced technical expertise.

A few visual analytics systems were developed specifically to deal with crime data. CrimeReports [cria] is a web system that allows one to visualize crime incidents that are stored in a database, which is populated and maintained by law enforcement agencies from the USA and Canada. As a system intended for the general public, it has a limited number of visual components and does not provide hotspot analyses. CrimeViz [Crib], another visual analytics system, has a set of visual components, which is similar to that of CrimeReports. In addition, it offers a tool for facilitating comparisons over time, where maps of different time periods are displayed as a slideshow. However, it does not support overlaying maps, nor does it include KDE-like components.

VALCRI is a semi-automated visual analytics system for crime intelligence analysis [val18]. VALCRI's user interface is based on the concept of thinking landscape [WWK17], where near regions give the details, and farther regions give the context. VALCRI shows concentrations of events as a set of circular clusters, accompanied by a bar chart that shows the quantitative variations over time [Bee15]. The regularity of circular-shaped clusters does not fit properly the real spatial crime density variations of a city. Therefore, it is not the usual representation of hotspots used by police departments.

CrimeVis is an interactive visualization system for analyzing criminal data [SSFGFPA*17]. The system is based on: choropleth maps for verification of concentrations; clustering algorithms for classification of the zones according to their level of criminality; and parallel coordinate charts for multi-dimensional analysis that compares jurisdictions. CrimeVis is an ongoing project that still lacks: analyses functionalities, such as KDE; and other essential analysis tools, such as spatial filters and annotations.

Visual Analytics Law Enforcement Toolkit (VALET) is a desktop suite of visual analytics tools for the exploration of police data sets [MMCE10]. VALET's spatial prediction functionality uses KDE, and its time series prediction functionality uses Seasonal-Trend composition based on LOESS (STL). More recently, VALET included correlation analysis of time-series [MME*12] and a new kernel for improving crime forecasting [MMM*14]. Despite its comprehensive set of features, VALET does not provide an easy way of comparing different analyses visually, forcing the users to create the analyses separately, to print them out, and to compare them side by side. VALET also lacks teamwork features, such as those for saving and sharing analyses.

Besides the visual analytics systems, in the literature one can find several ideas for producing hotspot maps and analysis tools. Hu et al. propose a predictive hotspot map based on KDE, whose kernel function includes, besides the distance-decay, a temporal-decay [HWGZ18]. For evaluation, the authors also introduced a new visualization for the Predictive Accuracy Index (PAI) [CTU08], called PAI Curve, which shows the index for a range of city area percentages.

Other approaches [BCH07, MRH*10, HWGZ18, NY10] proposed predictive crime hotspot maps based on KDE variations, while Godwin and Stasko [GS17] proposed a method for augmenting crime data analysis in urban spaces. They explored the concepts of paths, nodes and edges [LfUS60] in creating mental maps, which are built in cooperation with the community, and use raw data from police departments.

None of the discussed approaches visualize hotspots as set-like objects, although there are many techniques to visualize sets and their operations [AMA*14, Rod14, LGS*14]. SHOC represents relations among hotspots as set-like operations, based on Euler diagrams, because those diagrams are effective in representing containment, intersection, and exclusion visually [Rod14]. Euler diagrams are *well-matched* to hotspots, in the sense that the spatial relationships between the curves reflect the set relations precisely, a desirable property that renders those diagrams most effective [AMA*14, GUR99]. Also, using Euler diagrams is advantageous because they were already a familiar concept to SHOC's users, which facilitated their understanding of the relations between hotspots.

In summary, none of those approaches facilitate visual comparisons and do not meet the whole set of domain tasks and requirements that arouse from our collaboration with domain experts (see Subsection 3.1).

3. Problem Definition

Police have been changing in the last decades. The traditional strategies, which employ a large number of officers, act in response to incidents, and adopt random patrolling, are considered too passive and, often, are criticized for being expensive and ineffective [WEB*16]. Currently, police are trying to use methodologies, such as community policing, problem-oriented policing, and hotspot policing, in order to become more proactive [BS12]. All those techniques require a deeper understanding of the environment and a closer monitoring of crimes.

The literature already recognizes the importance of tracking the crime spatially and analyzing its distribution through time. Ratcliffe [Rat10], for example, states that "understanding the spatial dimensions of crime flux over time is a key component of cost-effective crime reduction in many situations." Chainey points out that users need to know where crime is increasing or decreasing [CR05], and where crime is fragmenting, expanding, or concentrating. Wortley and Townsley [WT16] declare: "understanding the role of criminogenic environments and being aware of the way that crime is patterned are powerful weapons in the investigation, control, and prevention of crime."

Based on interviews with our collaborators, acquiring this information and making it reach the officers' hands is a significant part of the problem. In Brazil, for example, almost all of the preventive police are under control of the state governments. Although each state is autonomous to organize its officers, usually police are divided into regiments, which are frequently overloaded, with no dedicated team for elaborating their planning (as we mentioned in the introduction). A typical decision that every regiment must take periodically is where to allocate preventive resources, considering whether it is daytime or nighttime, or whether it is a working day or a weekend. Making decisions this way is a continuous process, and they must always be reevaluating their allocation. Although they have a general-purpose GIS at their disposal, most of them do not use it for lack of technical skills. So, they prefer to develop plans based on a priori knowledge rather than spending their time operating intricate systems.

3.1. Domain Tasks and Requirements

Our framework's design is a result of the collaborative work among the authors, hereafter called researchers, and analysts and police officers, hereafter called domain experts. We created a system to perform the analytic tasks related to hotspots that domain experts conduct regularly. In this section, we present those tasks, and the requirements for the system.

We defined the tasks based on multiple semi-structured interviews and meetings with different people working with police agencies in both countries. Initially, we worked with the team of statisticians of a Brazilian police department, exploring their data and understanding their methods and current tools. Next, we attended the officers' periodic meetings, which are similar to a Compstat's meeting – "Crime Control Strategy Meeting." [WMM*03], and learned the different officers' perspectives on the data and how they planned their work. After about ten sessions and several rounds of visualization prototypes that took about one year, we determined the officers' needs and proposed a VA solution. Then, we spent 15 months in the USA to formalize a set of domain tasks, and to refine the proposed VA solution. Last, we perfected the domain tasks and the VA prototype with the Brazilian officers. The resulting domain tasks are:

- DT1 **Hotspot Identification and Comparison** consists in identifying priority areas of relative importance, the hotspots, and comparing pairs that represent different periods. They need to know which areas are changing from priority to non-priority and vice-versa, and which areas continue to be a priority. This task helps the police to reevaluate the allocation of their forces continually.

DT2 **Hotspot Evolution** consists in tracking the hotspot over time, using an absolute level of likelihood as the criterion. This comparison allows officers to identify expansions, contractions, and general movements of the crime, by the level of probability. This task helps the police to track more effectively the crime in both spatial and likelihood dimensions.

DT3 **Multi-Time Analysis** consists in identifying how crime is distributed in different periods of the day. Police usually consider this information when planning their movements during the day or when designing their shifts.

DT4 **Multi-Type Analysis** consists in identifying how different types of events correlate with one another spatially. This kind of identification can be useful in different ways. First, to deal with different types of crimes may require different approaches or specialized teams. Second, it is helpful to test hypotheses, such as the correlation between drug abuse and thefts in a given region. Third, it is useful in verifying whether police initiatives are synchronized with incidents.

DT5 **Multi-Level Analysis** consists in identifying regions based on increasing levels of likelihood. This task helps the police to reevaluate the number of resources deployed in each region.

In addition to the above tasks, during the process of designing our visual analysis tool, we identified the following requirements based on the domain experts' input:

R1 The tool should allow the types of events to be analyzed individually or in groups.

R2 The tool should allow analyses to be performed over selected regions of the city (the whole city or a part of it, e.g., a neighborhood or a district).

R3 The tool should be intuitive and straightforward, so that any officer can operate it easily, with minimum training and basic computer proficiency.

R4 The tool should allow annotations and sharing, so the analyses should be persistent and shareable.

We observed that officers in both countries had difficulties in performing the Domain Tasks using their available tools. In Brazil, for example, chiefs had to present and comment on crime evolution and resource allocation every other week in a meeting. After attending more than ten of these meetings, we recognized how difficult it was to discuss and answer questions using only charts, tables, and a base map. We never saw a KDE or even a point map in their presentations. They claimed technical difficulties for not developing more elaborated analyses. In the USA, on the other hand, the police worked closely with the community, and besides tracking crime in general, they were particularly concerned about the effectiveness of interventions. For example, they would like to track the impact of a new surveillance system in an apartment complex, with recurrent episodes of housebreaking, assault, and even shot. Their VA system did not provide an easy way of comparing time frames and of tracking whether the crime episodes were diminishing or moving. That kind of task – evaluating and adjusting interventions – can take months of work. So, annotating, saving, and sharing analyses would be useful features for their system to have.

Next, we describe our approach and the design choices involved in its development.

4. SHOC: the One-SHOt Comparison tool

We developed a visual analytics system (part of it is shown in Figure 1) that provides an interactive visual environment for encouraging data exploration. Users can visualize crime events in different ways, such as: point maps, choropleth maps, and density maps (KDE and MSKDE). The maps are organized in layers and can be made visible or invisible using the layer control shown in Figure 1(e). Those maps are fully configurable (control panels are omitted in Figure 1), i.e., the users can control colors and transparency, point size and shape, line borders etc. Also, our tool includes spatial and temporal filtering components for selecting the dataset to be analyzed, and an annotation component, which enables users to annotate their findings and plans directly on the map.

When officers started using our system to perform the domain tasks, they spent a lot of time for completing the comparative analyses. For example, consider a simplified DT3 scenario faced by every police department: to deploy resources for preventing robbery, considering daytime and nighttime shifts.

To help solving the root problem above using hotspot analysis, officers usually raise questions such as:

1. Where are the robbery hotspots during daytime and nighttime?
2. How many robbery incidents happened during daytime and nighttime last year?
3. What regions are common to both hotspots?

The answer to Question 1 defines where to deploy resources in each particular shift. The answer to Question 2 provides quantitative information, which is related to which proportion of resources they should consider allocating in each shift. The answer to Question 3 identifies regions where robbery is stable over time – no doubt; knowing where robbery is transient over time is useful, as well.

This simple analysis of a hypothetical DT3 case reveals that it could benefit from a spatial comparison tool, where users could examine the density level and spatial distribution of the hotspots of the shifts, separately or together, to identify correlations and coincidences.

Careful analysis of all other domain tasks shows that, similarly, they benefit from a surface comparison tool. In the current system, these types of comparisons would sometimes take a lot of cognitive processing from the users. They would build separate maps and make computations inside their heads. To avoid this cognitive overload, we developed a novel technique, called SHOC (the One-SHOt Comparison Tool), to make hotspot comparisons in a more direct way.

Below we describe how SHOC works, including the parameters and operations involved, and also describe how to perform a SHOC analysis and how SHOC helps to achieve the domain tasks.

4.1. SHOC's Overview

Figure 1 shows a typical SHOC analysis for comparing robbery in daytime and nighttime. SHOC performs the spatial comparison directly by superimposing two MSKDEs (MSKDE stands for Marching Squares Kernel Density Estimation, a technique that generates contour maps based on KDE maps [dQNSV16]), each one representing a hotspot map. The following properties of SHOC's design make it simple and effective:

- Computation of precise crime hotspot maps with MSKDE [dQNSV16].
- Using of contour lines to show, clearly, where the hotspot begins and finishes.
- Superimposition of MSKDEs with minimal occlusion to enable simultaneous analysis of the hotspots, identification of correlations, and exploration of the base map that is behind the polygons.
- Displaying of immediate spatial variations between the hotspots to release the user from making any visual comparison.
- Integrating of the analysis' results in one frame (shot), including hotspots, base map, and annotations, in order to facilitate printing and taking of pictures.
- Displaying of the difference and intersection of hotspots in a familiar Euler diagram form, in order to facilitate handling and interpretation. Stable regions (intersections) are shown as solid light yellow polygons, and regions that experience changes are shown fully transparent with their original borders (Figure 1).

4.2. SHOC's Parameters

SHOC has three parameters: cell size, bandwidth and contour threshold. In this section, we explain those parameters and their default values.

4.2.1. Cell Size

The cell size determines the resolution of the geographical space, i.e., its level of refinement, and affects only the map's visual appearance and the system's performance. Because cell size is independent of the bandwidth, it does not influence the levels of crime density in the cells.

When defining the cell size, the user has to take into account the trade-off between visual appearance and performance. Thus, the smaller the cell size, the higher the resolution of the map (smoother visual appearance and more refined polygons), and the worse the performance of the system will be. Our experience shows that 50 m or 100 m are values that provide a good balance between performance and visual quality. The cell size's default is 100 m.

4.2.2. Bandwidth

The bandwidth controls how far an event spreads its influence to nearby cells, i.e., the bandwidth defines the support of the KDE kernel function. Cells receive more density in maps with larger bandwidths, and those maps tend to form fewer and bigger density clusters, more suitable for strategic planning. On the other hand, a smaller bandwidth creates spotty maps, more appropriate for tactics. In SHOC, all hotspot maps in the same comparative analysis should use the same bandwidth so that the spatial comparison will be fair.

There is no consensus in the literature on which bandwidth value to use in general situations. Many works show values ranging from 150 m to 500 m [CTU08, Cha13, ECC*05, HZ14, CR05, BJP04]. SHOC adopts a default bandwidth value of 400 meters, which can be adjusted depending on the analysis' purpose: if more strategic, bigger values should be used; and if more tactic, smaller values should be used.

4.2.3. Contour Threshold

Users can set the contour threshold in two indirect ways:

- The user specifies the integral percentage of the density that the shapes should surround, and SHOC calculates the associated contour threshold; or
- The user specifies an MSKDE already created, and SHOC extracts the contour threshold level from it.

The choice of which option to use depends on the analysis the user wants to perform. Therefore, the user must understand how SHOC calculates the contour threshold to have full control over the study. We explain that in Section 4.3.

The default value of the contour threshold is associated with an integral percentage of the density equals to 30%. That value leads to a hotspot map coverage between 1% and 5% of the total area of the map, which is similar to the coverage of most hotspot maps found in the literature.

4.3. Computation of the Contour Threshold

In the original formulation of MSKDE, the threshold was calculated so that polygons surrounded a certain percentage of the map area. This paper extends the original MSKDE technique by providing two new ways of determining its threshold: first, the value is determined so that the MSKDE area includes a pre-specified percentage of the total weighted incidents (density); and in the second one, it is a specific value, defined by another MSKDE.

Figure 2 shows a hypothetical situation to illustrate how SHOC computes the threshold. The figure shows a region with a set of fifty-two events (small black circles); a colored KDE surface computed using the set of events; and an MSKDE map (three polygons) that was generated based on the KDE surface. The region of the KDE field is delineated by a dotted orange box and contains 42×44 grid cells, 139 of which are inside the MSKDE polygons.

The total contribution of weighted incidents of the field is approximately 183.8. The *threshold* delimits three disjoint regions inside three closed level curves. The *threshold* value could have been determined by one of the two different ways previously mentioned. If the *threshold* were to be determined using the percentage of the total contribution of weighted incidents, the user would have specified 30%, which means that the three level curves surround a total area containing approximately 55.1 of the contribution of weighted incidents. If the *threshold* were to be specified directly, the user would have specified a value of 3.25, which is the value of the *threshold* corresponding to the three level curves shown in Figure 2. Since this is just an illustration, all the two alternatives would give the same *threshold* of 3.25, and, inside the level curves, there would be 139 cells that account, together, for 55.1 as the contribution of the weighted incidents (30% of the total in the dotted region).

Table 1: *Variations on the Input Parameters to Perform SHOC*

Task	data set			MSKDE	Result
	Type of Event	Date Frame	Time Frame	Thereshold	
DT1	Same	Different	Same	Same Density Percentage	MSKDEs showing hotspots about different periods of time. Suitable for identifying regions with high concentration of density.
DT2	Same	Different	Same	Same Value	MSKDEs showing hotspots about different periods of time, with MSKDEs delineating at the same threshold. Suitable for tracking expansions, contractions and general movement of the density.
DT3	Same	Same	Different	Same Density Percentage	MSKDEs showing densities regarding different time frames throughout the day. Suitable for comparing shifts.
DT4	Different	Same	Same	Same Density Percentage	MSKDEs showing densities regarding different types of events. Suitable for identifying the spatial correlation between different types of incidents.
DT5	Same	Same	Same	Different Density Percentages	Similar to a topographic map, with MSKDEs showing, progressively, levels of priority.

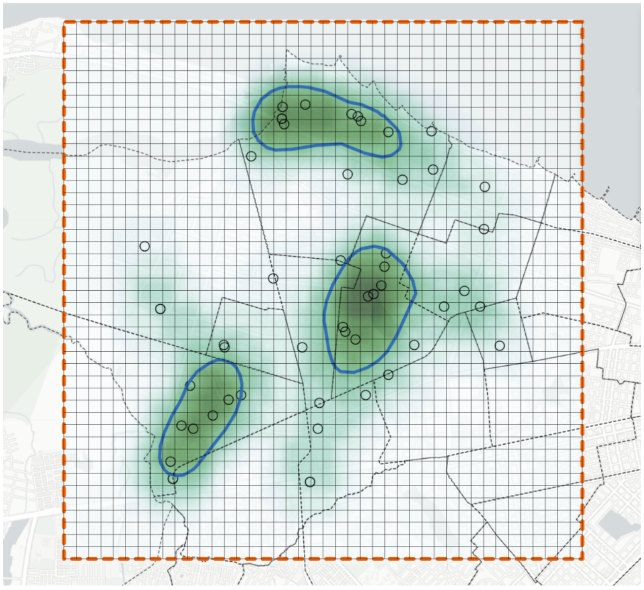

Figure 2: *An MSKDE map is composed of a set of polygons (shown in blue) enclosing hotspot regions. A KDE map is a 2D field of densities, colored according to a colormap (shown in green).*

4.4. Superimposing MSKDEs

SHOC gives information that helps to perform the domain tasks by identifying variations on superimposed MSKDEs, which represent different situations. For each domain task, SHOC needs a particular change between the MSKDEs, which is obtained by varying their input parameters.

Table 1 shows all the MSKDE input variations that SHOC needs to help to perform the domain tasks, one row for each domain task. Each row of the table informs, when superimposing two MSKDEs, which inputs should vary and which ones should be kept the same to produce the right contrast between them. For example, the first row shows that, if the user superimposes two MSKDEs that share the same Type of Event, Time Frame, and Percentage of Density (indicated by the value "same" in the corresponding columns in the table), varying only the Date Frame (indicated by the value "different" in the column "Date Frame"), the resulting visualization will expose differences between the hotspots of two different periods of time (column "Result"), which will help to perform DT1 (column "Task").

Users should be aware that, when comparing MSKDE maps regarding different date frames or time frames, periods should have the same range for comparisons to be fair. When comparing date frames, if possible, they should refer to the same period of the year, avoiding seasonality variations [MLP12].

At the end of the superimposition, SHOC also applies polygon intersection operations to compute the 3 sets of polygons that are of interest to analysts. Those operations are a subset of the topological relations framework proposed by Egenhofer and Franzosa [EF91]. Given two MSKDEs A and B, the following sets are computed:

1. Set 1: A - B, the polygons corresponding to the regions exclusive to hotspot A;
2. Set 2: B - A, the polygons corresponding to the regions exclusive to hotspot B;
3. Set 3: A ∩ B, the polygons corresponding to the regions common to both A and B.

Each set receives an appropriate visual encoding and is assigned to its own layer. Set 1 receives the same visual encoding as MSKDE A, Set 2 receives the same visual encoding as MSKDE B, and Set

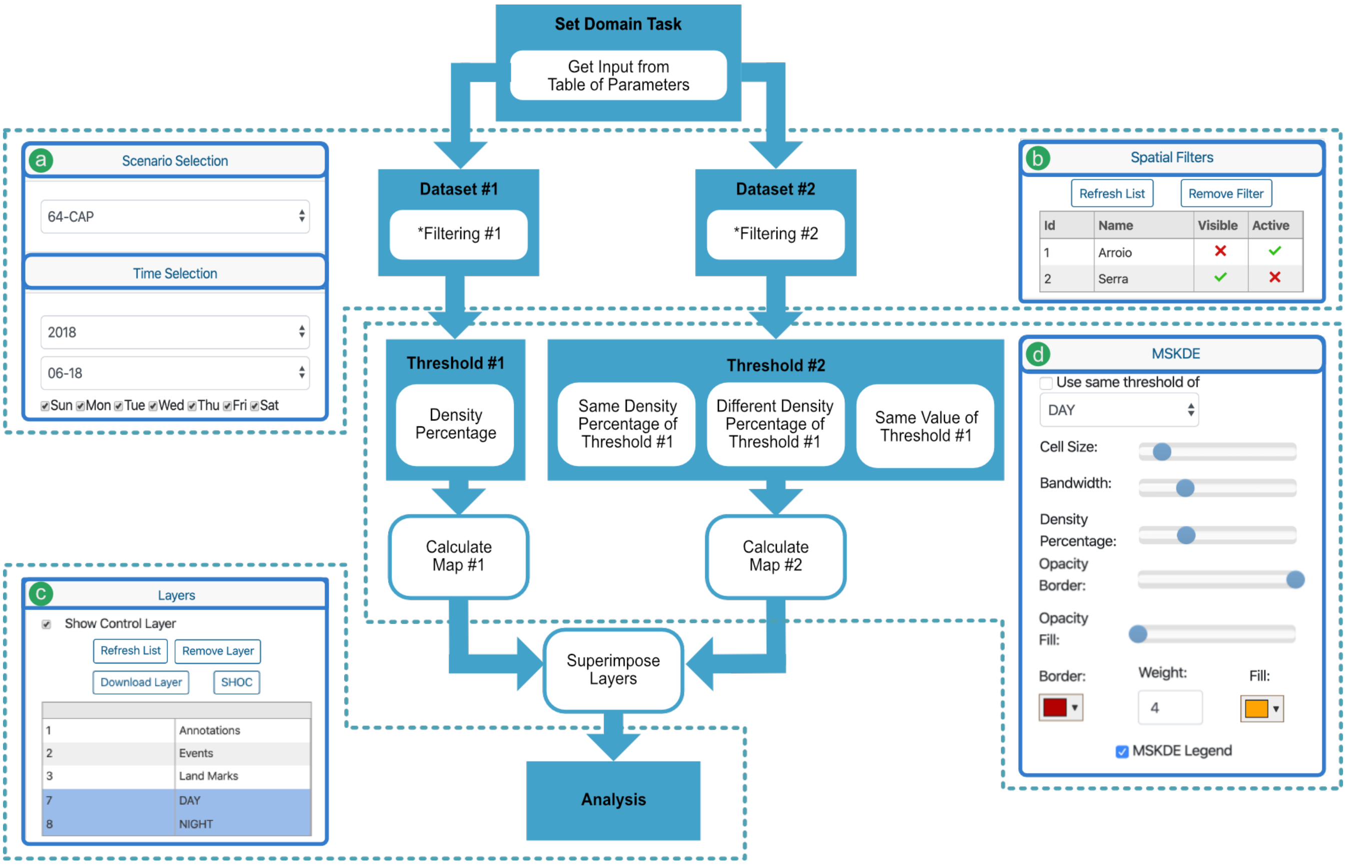

Figure 3: *Workflow for performing the Domain Tasks using SHOC: The *Filtering process is the application of filters regarding Type of Incidents, Date Frame, Time Frame, Days of the Week (a), and Spatial filters (b). Users create MSKDE layers using the MSKDE panel (d), all variations in only one page. In the Layers panel (c), users select which ones they want to apply set-like polygon operations (subtractions and intersections), facilitating hotspot analysis.*

3 receives a solid light yellow color. This design choice works best when only two MSKDEs are superimposed (a discussion is provided in Section 6.3) and favors the easy identification of the common regions without losing the context of the hotspots [AMA*14]. Users can always emphasize the other regions by manipulating the visible layers, as they can hide or show layers on demand.

4.5. Performing SHOC's analysis tool

In this section, we explain, in detail, how to perform any of the five Domain Tasks. Although this paper focuses on specific domain tasks, which were identified as the most relevant, we created a system that is flexible and easy of use. Therefore, we designed the interface and its components, so they are not tied to the five domain tasks, allowing users to create variations of those tasks or completely new ones.

Figure 3 shows SHOC's basic workflow and main interface components to perform any of the domain tasks as follows. First, the user chooses the domain task, learns the setup for it from Table 1, and decides what cell size and bandwidth to use in the analysis. Second, the user selects the first dataset by applying the following filters: a Scenario Selection filter, indicating the types of incidents; Time Selection filters, indicating date frame, time frame and days of the week (Figure 3a); and an optional Spatial Filter (Figure 3b). Third, the user creates the first hotspot by filling out the MSKDE panel (Figure 3d) with: cell size, bandwidth value, percentage of density for computing contour threshold, and some graphical choices (colors, opacity etc.). Fourth, after the first MSKDE is created, the user selects the dataset for the second hotspot, using the same Scenario Selection, Time Selection, and Spatial Filter tools. Fifth, with the second dataset on hand, the user goes to the MSKDE panel to create the second hotspot map by using one of the three strategies of defining the threshold. Sixth, after creating the hotspot maps, the user selects the two MSKDE layers in the Layers Panel and presses the "SHOC" button (Figure 3c).

After those six steps, SHOC computes the polygon operations and visually encodes them, generating three new layers. At this point, the user can begin exploring and annotating the analysis.

Figure 4 shows a description of the domain tasks using the typology of tasks from Brehmer and Munzner [BM13]. According to their typology, SHOC is a production task - it produces a set of

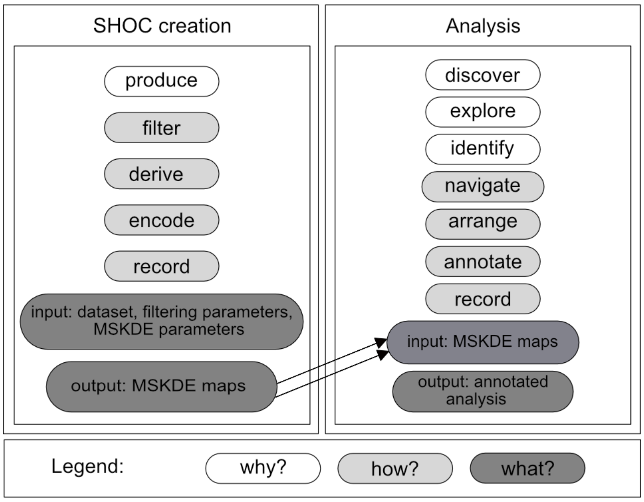

Figure 4: *Depiction of the domain tasks using Brehmer and Munzner's typology [BM13].*

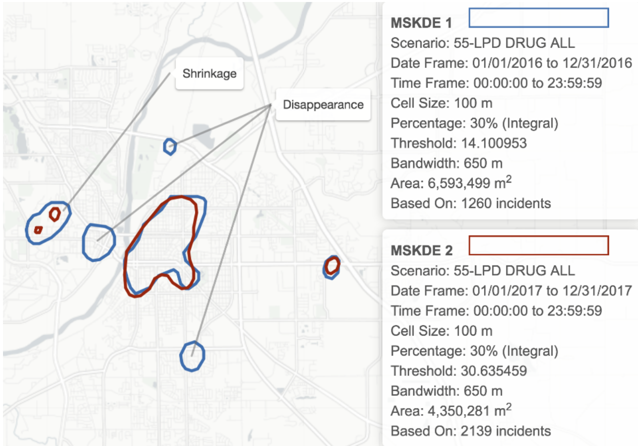

Figure 5: *The blue polygons represent the hotspot of 2016, while the red polygons represent the hotspot for 2017. The larger number of incidents in 2017 and the smaller area of the red polygons indicate that there was a concentration of the crime density from 2016 to 2017.*

MSKDE geometries that are used as input to the analytical part of the domain tasks. The analytical parts of the domain task are dedicated to exploration, identification, and discoveries.

For every Domain Task, SHOC immediately gives the spatial differences between the datasets. Officers do not need to make any extra visual comparisons. They can proceed to the next steps of the analysis, exploring the base map, together with the hotspot maps, their coincidences, and differences. SHOC, to facilitate the analysis process, also provides a legend for each hotspot map with the parameters that the user had set, the calculated threshold, the method for calculating the threshold, the area of the hotspot, and the number of incidents used to calculate the hotspot.

5. Case Studies

We present two real-world case studies to demonstrate that SHOC helps to perform the domain tasks.

The first case study concerns the problem of drug abuse in Tippecanoe County, Indiana, USA, during the years of 2016 and 2017; the second case consists of two analyses used by a police department in Brazil to plan the patrol of a beat (a geographic area designated by the police department) to fight Crimes Against Property (CAP) and Crimes Against Life (CAL). All cases deal with crime problems that are relevant in many cities around the world nowadays.

5.1. Drug Abuse in Tippecanoe County, USA (2016-2017)

This example is one of the several study cases that we developed together with the Lafayette Police Department (LPD) and the Purdue Police Department (PUPD), in a series of 8 meetings between November 16, 2017, and May 23, 2018. It used a prototype version of SHOC that did not display the differences and intersections using different visual encoding.

The police knew that the recorded number of drug abuse incidents was increasing, and they wanted to know more about how and where that increase was taking place. For making the comparisons, we partitioned the data set, which included all the incidents recorded from January 1, 2016, to December 31, 2017, into two partitions. The first partition contained the 1,288 incidents of 2016, and the second partition contained the 2,129 incidents of 2017.

We performed domain tasks DT1 and DT2, comparing the two partitions. For that, we used the following parameters: percentage of the total weighted incidents equal to 30% (that value was used to compute the threshold for both MSKDEs of DT1 and the first MSKDE of DT2); and bandwidth of 650m (that bandwidth was appropriate because the study region comprised the whole county).

5.1.1. Hotspot Identification and Comparison (DT1)

Figure 5 shows MSKDE maps for partitions 1 (2016, in blue) and 2 (2017, in red). Despite the increase of nearly 70% in the number of incidents from 2016 to 2017, the smaller total area in 2017 indicates that drug abuse incidents are more concentrated in 2017 than in 2016. The increase in the *threshold* from 14.10 to 30.64 confirms that concentration. Notice that, in Figure 5, there are two larger polygons (one red and another blue), whose shapes are almost coincident. However, the crime density level on the red border is more than twice that on the blue border. The disappearance and shrinkage of polygons from 2016 to 2017 do not necessarily indicate a reduction of crime density in those areas, but, rather, a decrease in their relative importance concerning the entire community. Finally, the analysis suggests that the central region of the map is where the priority with regard to actions against drug abuse should be focused in the county.

5.1.2. Hotspot Evolution (DT2)

Figure 6 depicts partitions 1 (2016, in blue) and 2 (2017, in red). The comparison shows that the MSKDE of 2017 has more than

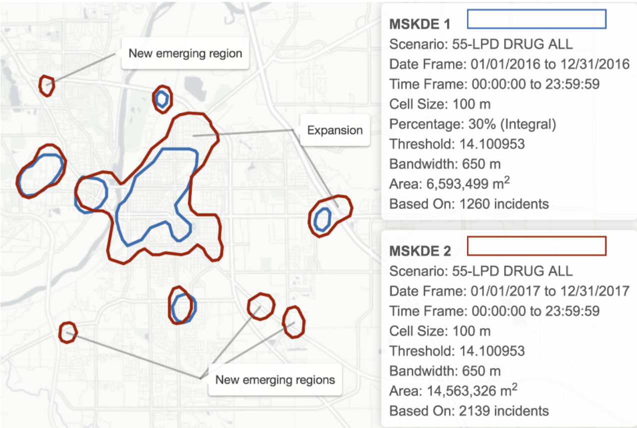

Figure 6: *The blue polygons represent the hotspot for 2016, while the red polygons represent the hotspot for 2017, using the same threshold level of the blue polygons. The larger area of red polygons indicates the expansion of the crime density from 2016 to 2017.*

twice the area of the MSKDE of 2016. That indicates the spreading, in 2017, of the regions with crime density above the level of 14.10. The MSKDE maps also indicate changes in shape and number of polygons. The larger central polygon is expanding and enclosing the other polygons. Additionally, in 2017, there are four new emerging regions of high crime density, which did not exist in 2016. Finally, the comparison shows that, using 2016 as a reference, drug abuse in 2017 has expanded geographically, with indications of where the expansion took place.

5.1.3. Conclusions

Based on both domain tasks, we can conclude that drug abuse crime was prevalent in the central area of the city and expanded there from 2016 to 2017 with even higher concentration. Some new high concentration areas emerged in other points of the city. The substantial increase in the number of incidents indicates the need of a strategy change.

5.2. Crimes Against Life and Property in Brazil

The police department of a city in Brazil divided the city into ten beats, each with its police resources. In this use case, officers of one of the beats (Beat F) used SHOC to improve the understanding of the criminal context and define priority areas and time frames to patrol two kinds of incidents: Crimes Against Life (CAL) and Crimes Against Property (CAP). Because of space constraints, we show only the main aspects of the complete analysis in this paper.

Concerning social and economic development, Beat F can be roughly divided into three zones (see Figure 9): Zone A, in the northwest, which is the most developed area; Zone B, alongside the right border, with intermediate development; and Zone C, in the middle and southwest, which is the less developed sector. In the officers' opinion, the different social and economic levels have a significant impact on the distribution of events in the Beat.

In all the analyses, officers applied a spatial filter to extract only the events inside Beat F. They also used a temporal filter: for CAP analyses they restricted events to the period from January to November of 2018; and for CAL analyses, from June to November of 2018. Due to the size of the Beat (21.01 km^2), they choose a bandwidth of 400 m.

5.2.1. Crimes Against Life (CAL)

In our initial engagement in the activities of Beat F for analyzing CAL, due to a critical situation with a consistently high number of homicides per month, the Police Department had already started a project to reduce the homicide rate, named the "Stanch Project." That project's strategy was to select parts of the Beat (called "quadrants") and a single time frame (limited to a continuous range of 6 hours) and deploy much more resources than usual there, borrowed from other Beats. The duration of the Stanch Project was only 15 days, but, due to good initial results, the Police Department was committed to launching a new phase of equal duration immediately after the first phase was finished. When we started our activities, the first phase was already in progress. Therefore, we only helped the police to define the quadrants and the timeframe for the second phase. We decided not to perform the analyses ourselves, but, instead, to offer training sessions to the officers, and let them perform the analyses and define quadrants and timeframes, with our support. Following instructions from the Chief, despite being CAL the focus of the project, whenever possible, CAP was also taken into consideration. The analytical process happened as follows:

Exploratory analysis: Following our recommendation, officers conducted an activity in which they were free to create any analyses for the CAL and CAP scenarios. The purpose was to make the officers more aware of the spatiotemporal distribution of incidents, and to promote discussions among themselves and to let them draw comparisons with their a priori knowledge. The result was surprising: they created dozens of analyses, even exploring some possibilities that we had not included in the training sessions, such as an expanded spatial filter to examine the vicinity of the Beat. As an example of their exploration, Figure 7 presents a multi-level analysis (DT5) for the CAL scenario with two percentages of the total weighted incidents: 25% and 75%, where they could compare SHOC outlines on resource allocation to their current policy.

Date frame and time frame definitions: In order not to lose the perception of the most recent homicides' dynamics in Beat F, the officers decided to use only the last six months of available data: from June to November of 2018. They defined the time frame as the hottest six-hour continuous interval of the CAL histogram, which was the 18h-24h time frame.

Quadrants' definition: The officers created a multi-type analysis (DT4) that included both CAL and CAP and used 40% of the total weighted incidents. Next, they compared the DT4 study with the quadrants of the first phase of the project. Finally, they determined the new quadrants based mainly on the CAL layer of the DT4 analysis. However, they adjusted those quadrants to contemplate some parts of the CAP layer as well as a few regions outside the DT4 polygons that would benefit from the police's presence because of the high tension between rival gangs.

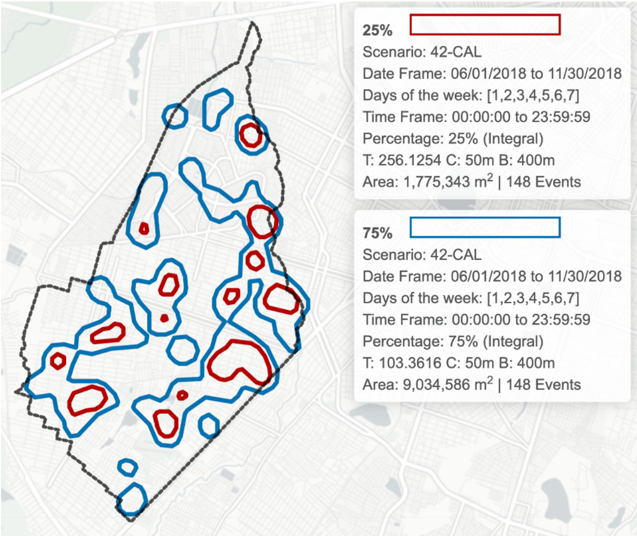

Figure 7: *DT5 analysis for the CAL scenario in Beat F. Red polygons surround areas that comprise 25% of the crime density, while blue polygons surround regions that include 75% of the crime density. The spaces between the red and blue borders account for 50% of the crime density and the rest of the Beat, 25%. Officers can identify regions at three different levels of crime density, facilitating resource allocation.*

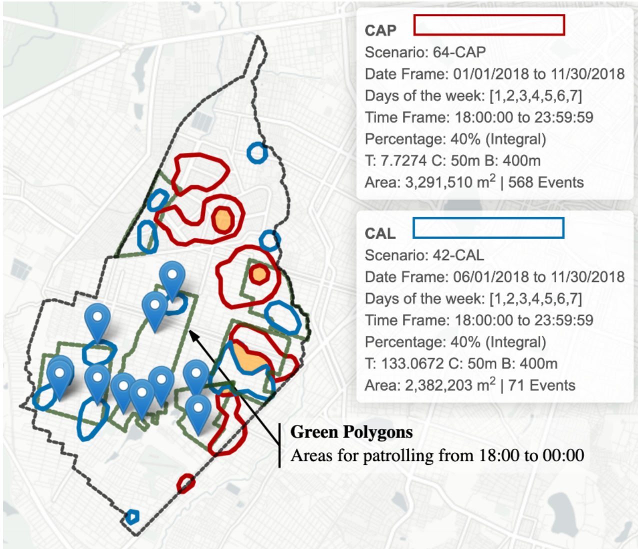

Figure 8: *Multi-type analysis (DT4) to help define quadrants. Quadrants have green borders. Blue icons indicate high-tension places that were included based on a priori knowledge.*

Figure 8 shows the officers' analysis for the definition of quadrants. The officers used the annotation system to draw the new quadrants (green borders) and to mark the regions of high tension (blue icons). Due to the small size of the image, we omitted the textual annotations to make it easier to interpret. Notice the spatial difference between the hotspots for CAL and CAP. In this analysis, crimes against properties are more concentrated in affluent regions while crimes against life are more frequent in impoverished regions (see the zones in Figure 9), a situation similar to the one observed by Balbi and Guerry in their pioneer study [BG29].

5.2.2. Crimes Against Property (CAP)

For analyzing CAP, officers created a histogram that shows the number of crimes at each hour and selected the two hottest four-hour periods to concentrate their efforts: the first period, in the morning, from 5:00 to 9:00 (people going to work and school) and the second, around noon, from 11:00 to 15:00 (people going out for lunch or returning from school). For the exploration of the differences between the two time frames, they created a multi-time analysis (DT3) with a percentage of 40% of the total contribution of weighted incidents. Figure 9 shows the DT3 analysis.

From the DT3 analysis, officers acquired some new information. For example, they observed CAP concentration in Zone A in the morning but not around noon. They thought that happened because people living in Zone A usually do not need to move too far away from their homes to go to school or to go to work early in the morning, so they are less vulnerable in the first period. On the other hand, people of zone B do need to move in the morning and become more vulnerable. Officers thought that CAP rises around noon in Zone A because of the numerous businesses and schools in the area, which attract criminals in these periods. They believed that Zone B also presented a high CAP rate around noon because of its peculiar geographical location, which connects Beat F to the rest of the city (right border). So, there is always a significant flow of people and vehicles through Zone B. Zone C is almost free of CAP hotspots because of the weak economy, a place less suitable for crimes against property.

To help planning the resource allocation, they created a multi-level analysis (DT5) for each period, using 25% and 75% of weighted incidents. Figure 10 shows the multi-level analysis for the period from 5:00 to 9:00, which gives indications on where are, proportionally, the CAP density.

6. Discussion

In this section, we present the feedback received from domain experts during the development process and execution of the use cases, followed by a discussion on the differences between the police of the two countries and the impact of using the system. We also discuss the limitations of the tool.

6.1. Domain Expert's Feedback

Officers expressed excitement with the possibility of comparing, on the same screen, hotspots for different time frames or different kinds of incidents. In their opinion, it is easier and more accurate than comparing two hotspot maps side by side.

The LPD's Chief and the Crime Analyst told us that SHOC would be useful in the frequent task of evaluating the impact of initiatives (DT2 is particularly useful). They thought that quick and

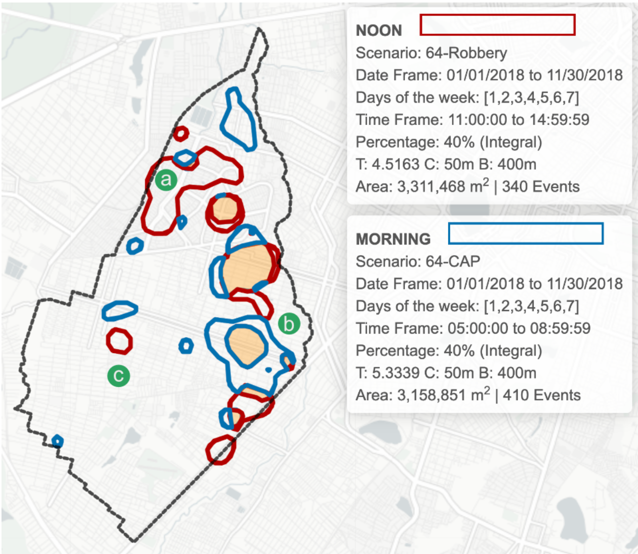

Figure 9: *Multi-time analysis (DT3) for crimes against property in Beat F. The different zones, based on their social and economic development, are indicated with labels: Zone A, in the northwest, is the most developed area; Zone B, alongside the right border, is intermediate; and Zone C, in the middle and southwest, is the less developed area.*

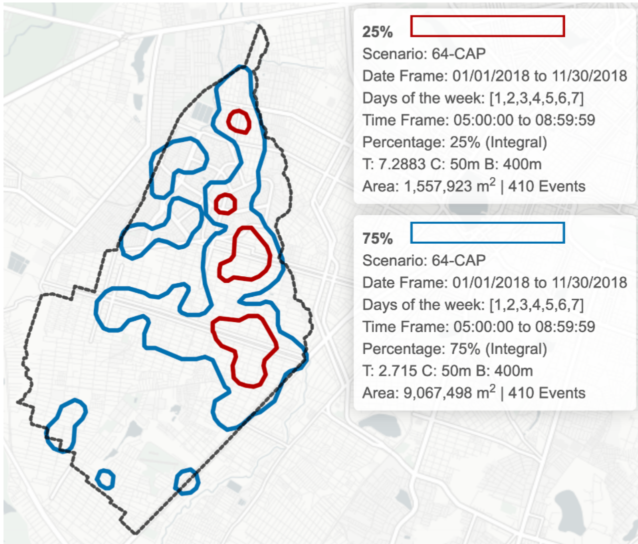

Figure 10: *Multi-level analysis (DT5) for crimes against property in Beat F, in the morning. The four red polygons include 25% of the density whereas the big blue polygon encloses 75%.*

precise visual comparisons facilitated the assessment of actions and strategy changes.

Officers considered that SHOC would have a positive impact on routine activities. They believed that tracking the crime phenomena with SHOC would lead to improvements in patrol planning and, therefore, to better resource allocation.

The LPD's Chief and both Captains in charge of patrolling pointed out that easily making comparative analyses in SHOC is useful for decision-making regarding shifts. To keep the shifts as efficient as possible, they need, for example, to compare crime density between daytime and night-time and between working days and weekends. They agreed that SHOC facilitates those comparisons.

The LPD's Specialist in Crime Prevention also remarked that the annotation layer would improve communication and teamwork. For example, an officer A would annotate a given analysis and, later, an officer B could have insight into the analytical process used by A, even without any help from officer A.

The LPD's crime analyst requested us to simplify the interface regarding the number of input parameters, allowing, for example, the use of the city's or office's profiles to set some parameters automatically. He believed that officers would feel more confident in using the system when they understood everything in the interface.

6.2. Impressions about differences and similarities between the Brazilian and the American police environments.

In general, we observed more similarities than differences between the two environments. Regarding the distribution of incidents, the spatial and temporal concentrations are similar, varying the kind of events. We noted that, in the USA, the police are closer to the community, sharing more data, and making some discussions together [SdQNWE18]. In both countries, they are conscious of the benefits of hotspot policing. Regarding officers' profiles, we found officers with a high level of interest and willingness to use the system in every police department. However, they were always pressed for time, and prioritized being on the streets.

We believe that SHOC would be useful in many police departments around the world since hotspot policing is suitable for fighting most types of crimes. Our approach is straightforward, and with only a few clicks, an officer can create an analysis that is easy to be interpreted. They can also fully annotate and share it with colleagues, improving the knowledge of the police department.

6.3. Limitations

Although there are specific rules about parameters, SHOC is still not pure enough concerning this point. Officers have to set cell size, bandwidth, and the density percentage, which is not natural for some of them.

As we pointed out, SHOC computes polygon operations, such as intersections and subtractions, for two MSKDE layers, and the resulting pairwise comparisons satisfy the requirements of the officers. Nevertheless, this is more a matter of taste than of a system limitation, since SHOC is capable of creating and visualizing as many layers as desired. Moreover, the user can easily hide and show layers using the layer control interface. In fact, users often create many layers per analysis, showing some of them on demand. However, in our experience with the officers, visualizing more than three MSKDEs at the same time is not recommended because of clutter.

SHOC is based on MSKDE, which is a contour and, therefore, it does not include the spatial distribution of the weighted incidents contribution inside the polygons. To minimize that limitation, we included in the visual analytics system, a KDE generator. With that, users can, on-demand, show, and hide a KDE layer and look for noticeable concentrations inside the polygons that could have an impact on the analysis.

7. Conclusions and Future Work

In this paper, we provided a characterization and abstraction of the hotspot analysis problem into five domain tasks and presented SHOC, a tool that facilitates performing the domain tasks by giving a straightforward way of making spatial comparisons, using set-like operations on superimposed geometries. We demonstrate SHOC effectiveness in two real case studies that helped police departments on planning their preventive initiatives for high relevance public safety issues.

Based on the feedback of the users during the initial deployments of SHOC, there are different opportunities for future work. First, we would like to improve the interface in different ways. For example, to simplify parameter selection, we would like to make use of profiles, for both users and geographic regions. Also, when sharing analyses with non-analysts and other stakeholders, it would be desirable to display a simplified version of the interface with fewer controls. Second, we identified that, as users' analyses start to become more sophisticated, they will need a more advanced annotation system. We plan to enable provenance, encryption, and support semantic queries on the annotations. We also plan to support multiple annotation layers in the analyses. Third, we plan to incorporate animation techniques and controls to display the evolution of the hotspots over time as an animation that users can pause and playback at selected time frames to help them perform further investigation. Finally, we plan to incorporate a statistical test to identify false-positive hotspots and custom analyses involving machine learning techniques for the prediction of crimes.

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