

Visual Analytics for Urban Crime Analysis

Germain García Zanabria

Advisor: Prof. Dr. Luis Gustavo Nonato

Instituto de Ciências Matemáticas e de Computação
USP - São Carlos

» Outline:

- Introduction/Motivation
- Crime Data
- Contributions
 - CrimAnalyzer
 - Mirante
 - CriPAV
- Conclusions

» Introduction/Motivation

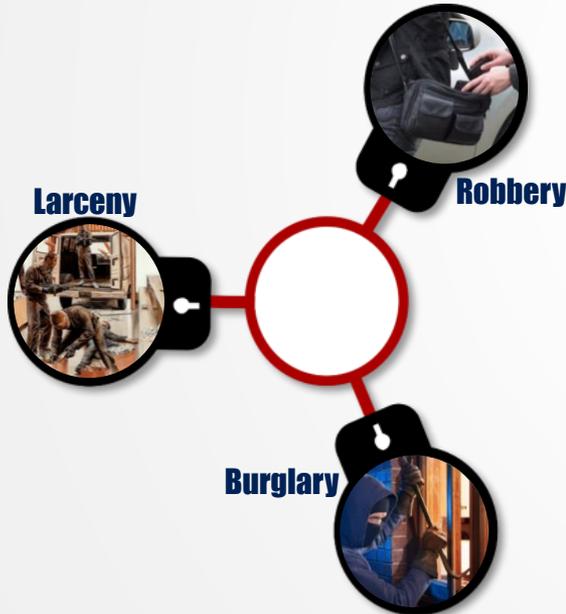
Crime

Crime can be defined as breaking or breaching of criminal law (penal code) that governs a particular geographical area (jurisdiction) aimed at protecting the lives, property, and the right of citizens in that jurisdiction [1].

Crime is an offense against a person, or his/her property, violation of socially accepted rules of human ethical or moral behavior.

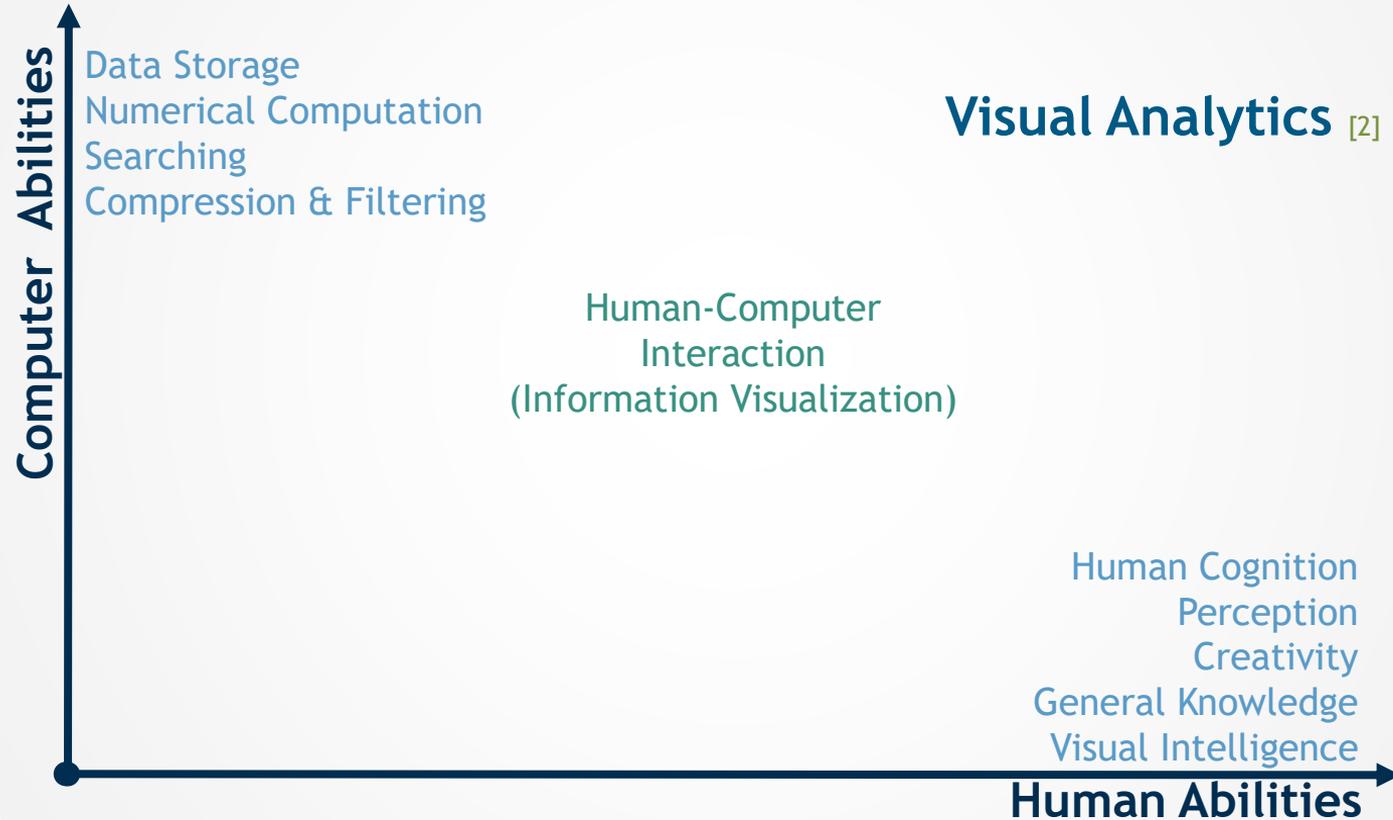
Law enforcement agencies deploy resources in a more effective manner to:

- Prevent
 - Control
 - Reduce
- Crime activities



» Introduction/Motivation

Search for patterns, trends, structure, irregularities, relationships among data

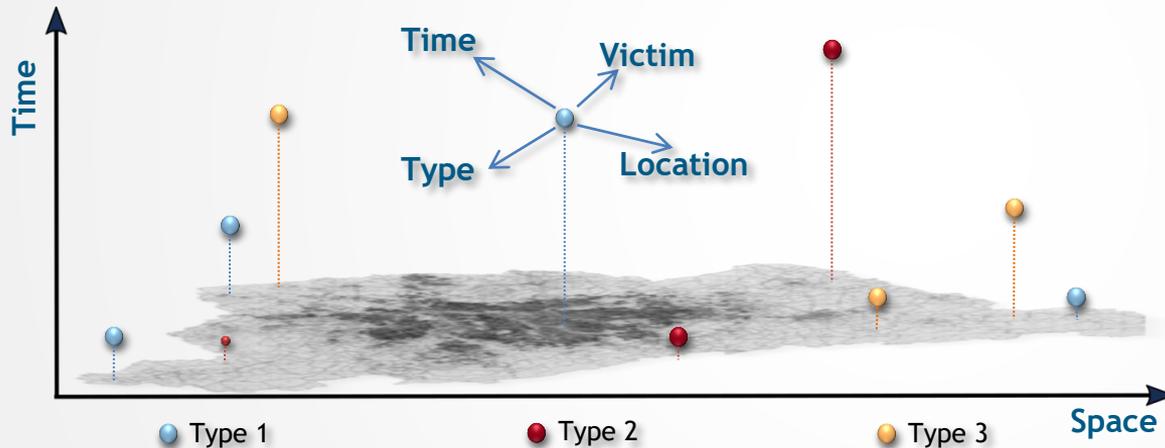


Keim et al. (2008)

» Introduction/Motivation

Crime Mapping

A branch of Geographic Information System (GIS) devoted to explain spatio-temporal behavior of crime activities.



Allows

- Demonstrate the importance of local geography for crime frequency and type.
- Identify and visualize hotspots.
- Identify the seasonality of crime types in certain locations.

[3,4]

» Introduction/Motivation

Brazil is a dangerous place, with a high murder rate and surprisingly high disparity when compared against other large countries*.



NEV



» Data Set 1 - São Paulo

● From **2000** to **2006**

● The data set contains **3 attributes**:

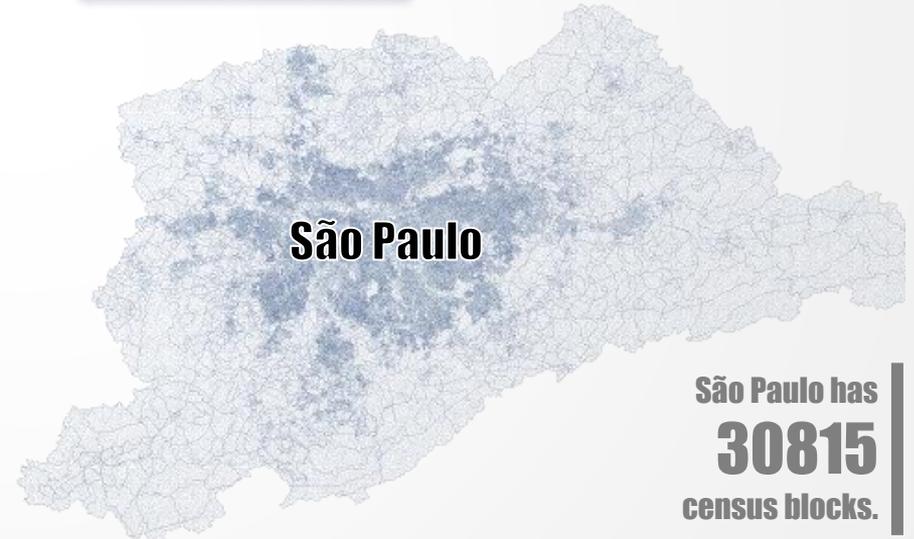
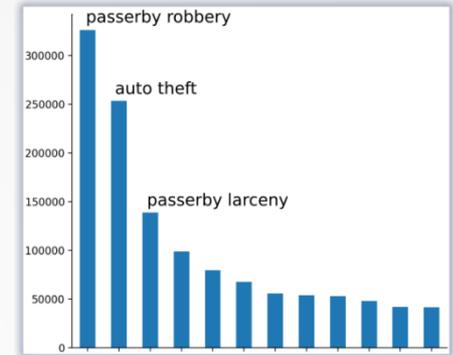
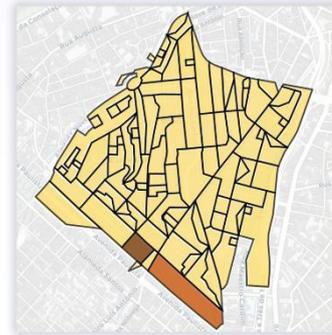
- Census unit code where the crime happened.
- Type of crime.
- Date and time of the crime.

● **Crime types** range in **121** categories:

- Passerby robbery
- Auto theft
- Larceny
- ...

● **Categories** are:

- Roubo - **691 954**
- Furto - **587 885**
- Roubo de veículo - **295 081**



» Data Set 2 - São Paulo

● From **2006** to **2017**

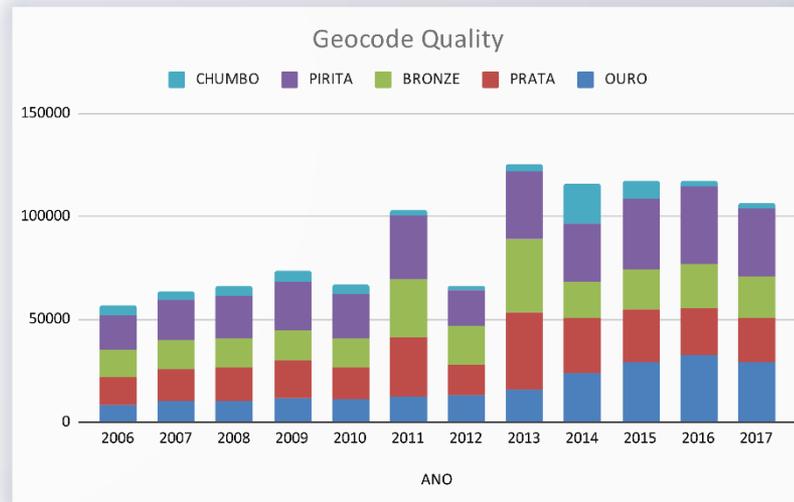
● **Attributes:**

- ANO_OCORR: Year of occurrence.
- DATA_OCORRENCIA_BO: Date of occurrence.
- HORA_OCORRENCIA_BO: Hour of occurrence (many of them nominal: Madrugada, manhã, Noite).
- NOME_DELEGACIA_CIRC: Station name
- RUBRICA: Crime type (**16** types)
- FLAG_STATUS: Status (consumado).
- COD_SETOR: Code of census block
- COORD_X: lat
- COORD_Y: lng

● **Crime types** range in **3** categories:

- Passerby robbery
- Commercial establishment robbery
- Vehicle robbery

São Paulo has
30815
census blocks.



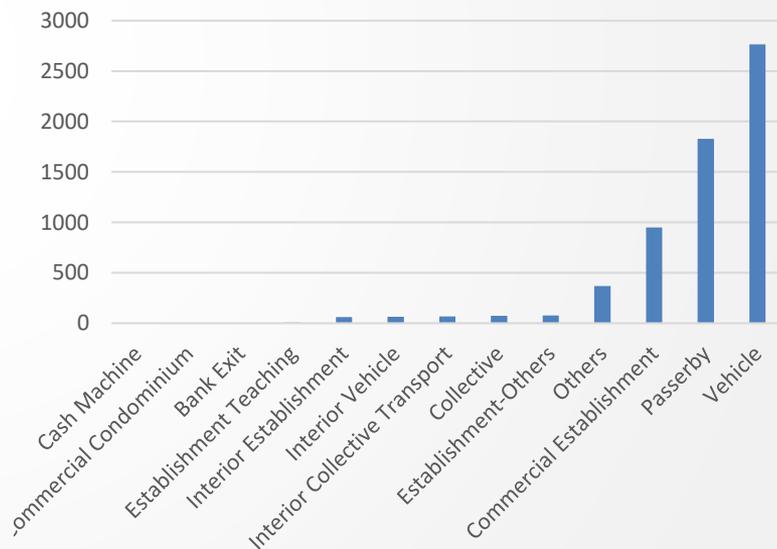
» Data Set 3 - São Carlos



• Data set from **2014** to **2019**

• Attributes:

- **ANO:** Year of occurrence.
- **DATA_OCORRENCIA_BO:** Date of occurrence.
- **HORA_OCORRENCIA_BO:** Hour of occurrence.
- **FLAGRANTE:** Flagrant
- **CONDUTA:** Type of crime (**13** types)
- **LATITUDE:** lat
- **LONGITUDE:** lng



*The focus of this thesis is to study and analyze crime patterns considering different factors. To do this, we have to sort out different crime analysis problems: **hotspot definition and detection, space discretization, and spatio-temporal dynamics.***

» Introduction/Motivation

Hotspot definition and detection

Given the crime events in an urban space, we propose different methods (depending on the spatial discretization) to identify and present hotspots considering not only the intensity but also the frequency of crimes;

Space discretization

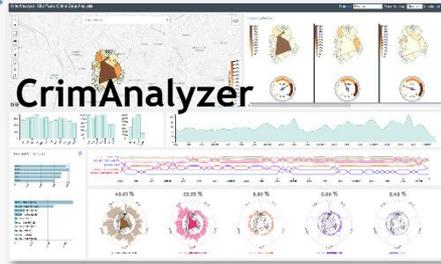
Different domain discretization, switching from grid-based to a street-based spatial discretization;

Spatio-temporal dynamics

Spatio-temporal crime patterns analysis, supported by visualization and machine learning mechanisms to extract and visually present different spatio-temporal patterns.

» Introduction/Projects

NEV
2000
2006



Data Set - 1

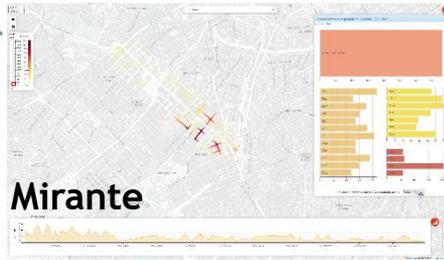
Non Geo-referenced data

Geo-referenced data

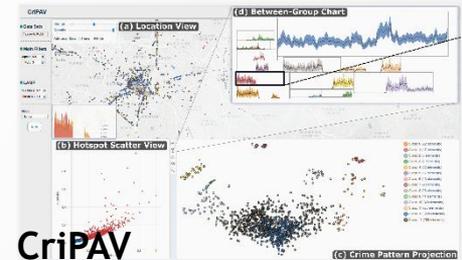
2006
2017



2014
2019

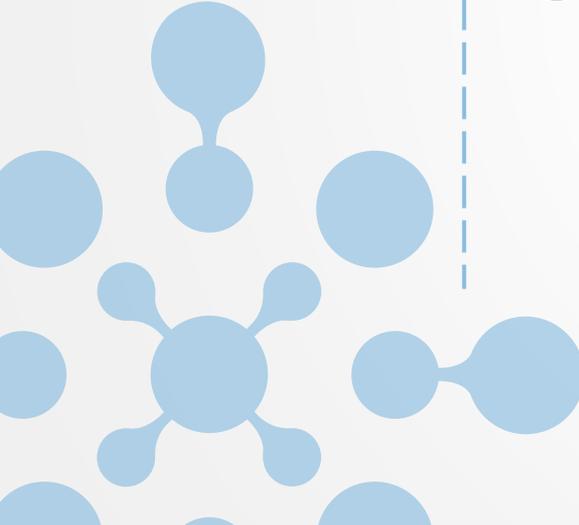


Data Set - 2 and 3



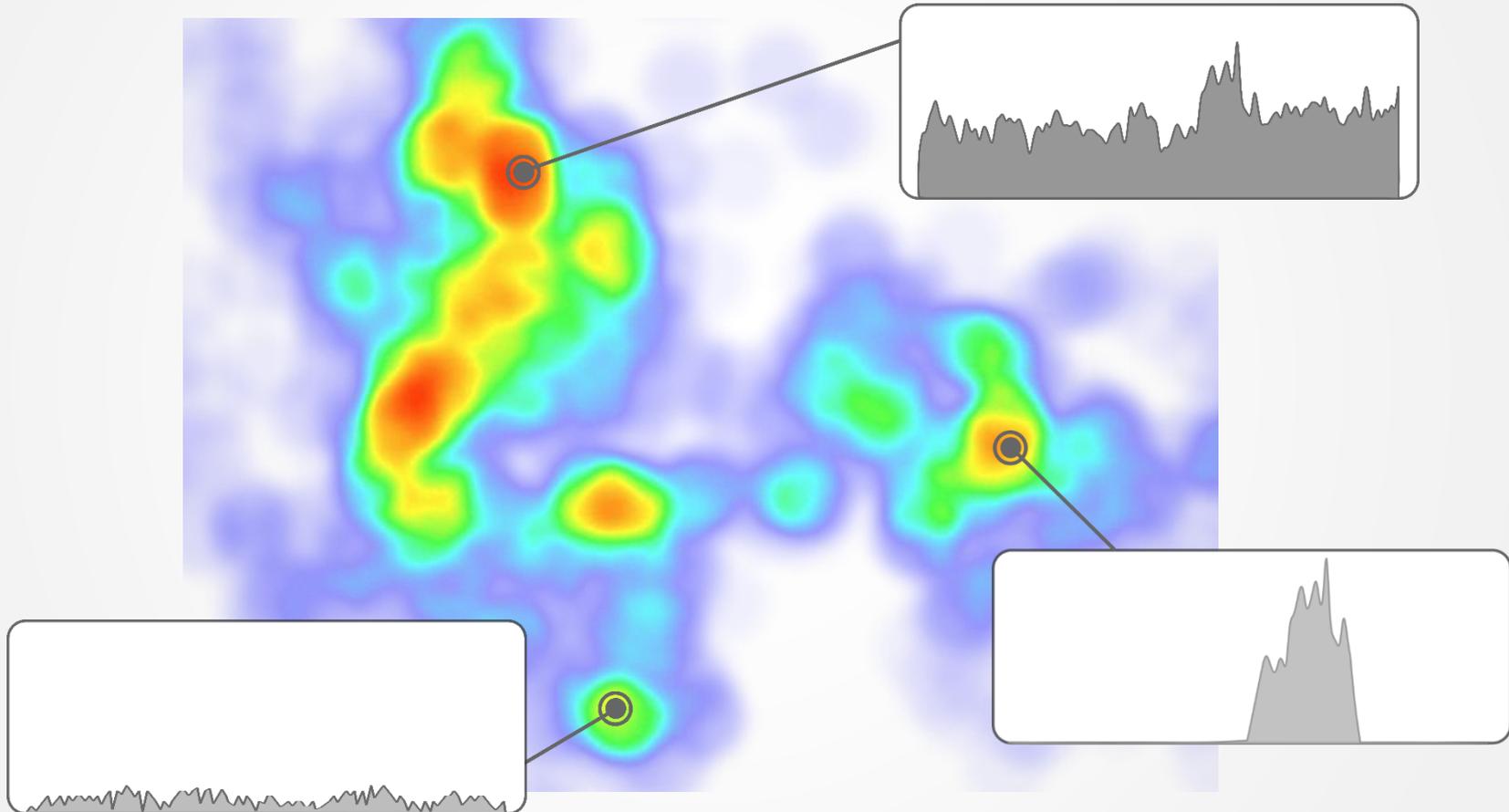
NEV
2006
2017

Data Set - 2



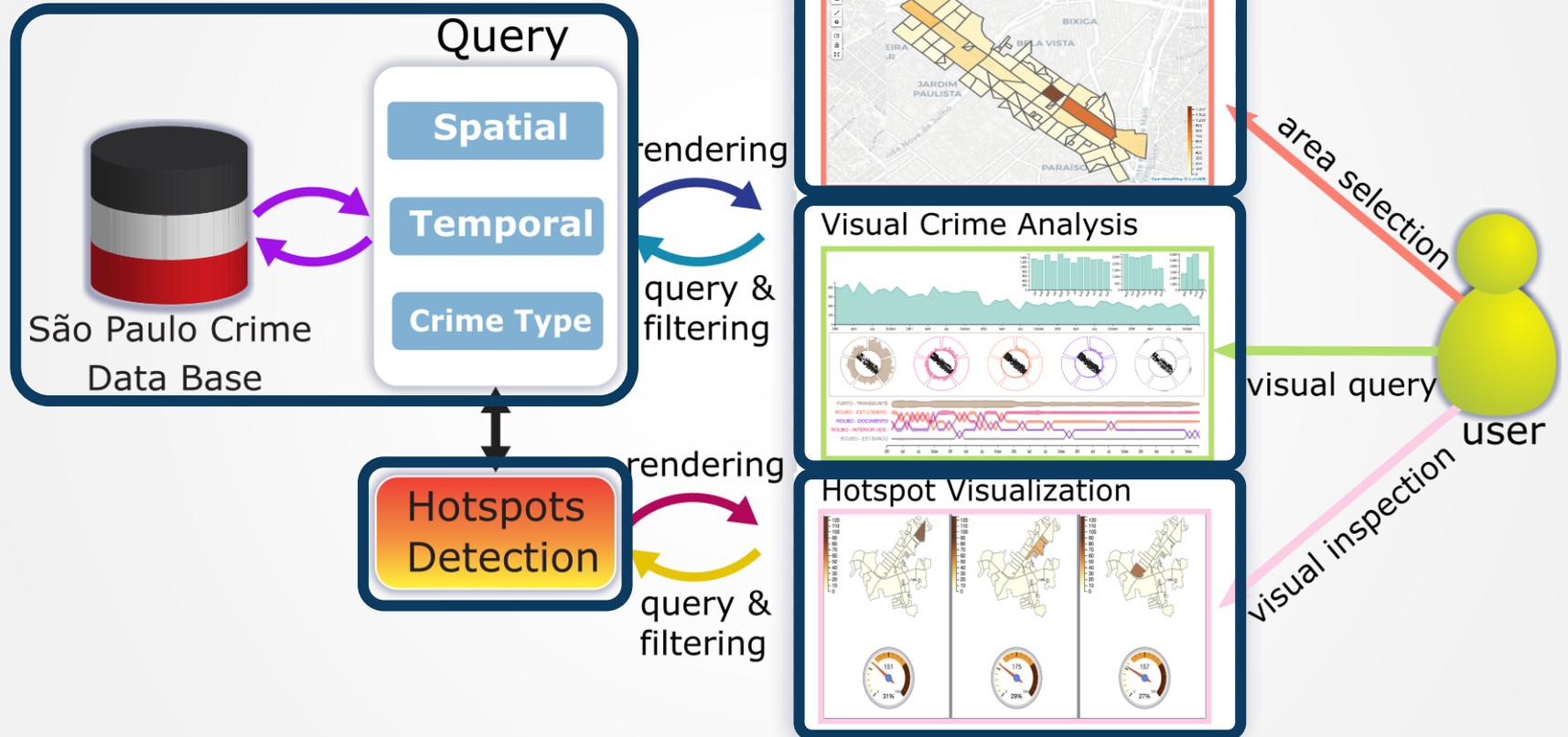
CrimAnalyzer

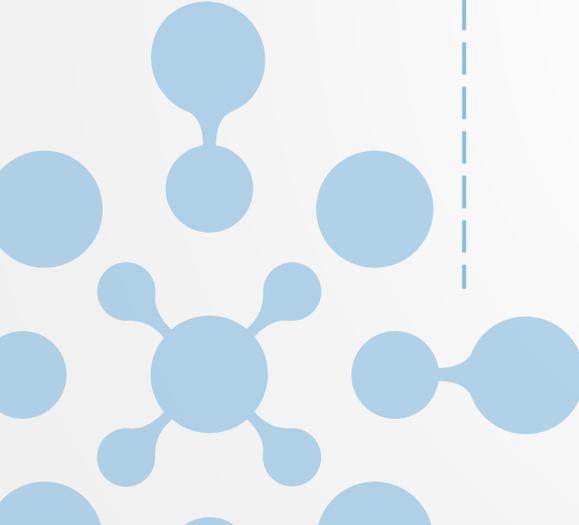
» CrimAnalyzer - Problem Analysis



» CrimAnalyzer - Pipeline

User Interface





CrimAnalyzer

**Hotspot Identification
Model**

» Non-Negative Matrix Factorization (NMF)

An $m \times n$ matrix X is said *non-negative* if all entries X are greater or equal to zero ($X \geq 0$). The goal of NMF is to decompose X as a product $W.H$, where W and H are *non-negative* with dimensions $m \times k$ and $k \times n$, respectively.

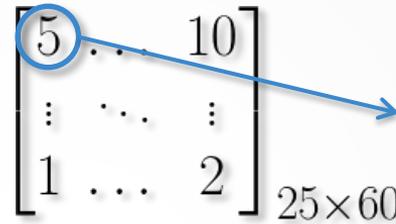
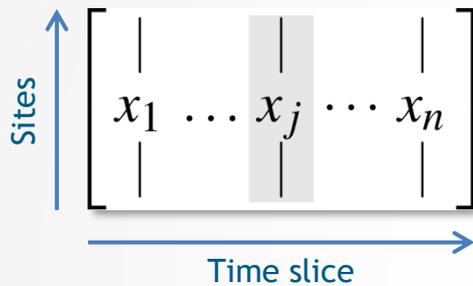
$$\arg \min_{W,H} \|X - WH\|^2 \quad \text{subject to} \quad W, H \geq 0$$

The diagram shows the decomposition of matrix X into matrices W and H . Matrix X is represented as a row vector of columns $x_1, \dots, x_j, \dots, x_n$, with the x_j column highlighted in grey. This is equal to the product of matrix W and matrix H . Matrix W is a row vector of columns w_1, w_2, \dots, w_k , with w_1 highlighted in orange, w_2 in yellow, and w_k in purple. Matrix H is a row vector of columns $h_1, \dots, h_j, \dots, h_n$, with the h_j column highlighted in grey. The h_j column is further divided into segments h_{1j} (orange), h_{2j} (yellow), and h_{kj} (purple), representing the coefficients for the basis vectors w_1, w_2, \dots, w_k in the linear combination for column x_j .

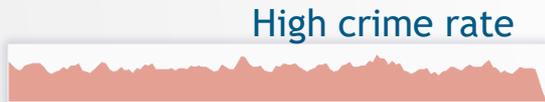
A set of basis vectors w_i (columns of W), and a set of coefficients h_j (columns of H), such that each column x_j of X is approximated as linear combination $x_j \cong \sum_i h_{ij} w_i$, (or $x_j = Wh_j$) [22].

» Identifying Hotspot with NMF

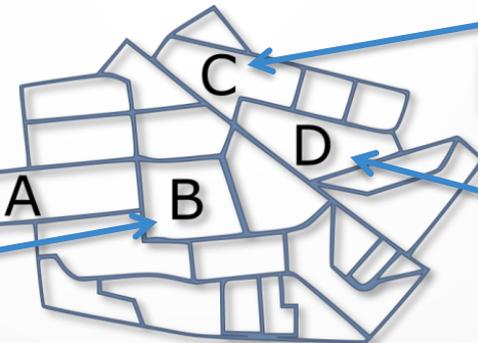
NMF to identify hotspots, their frequency and “intensity”. The matrix X to be decomposed as the product $W.H$ comprises crime information in a particular region of interest.



First site has 5 crime activities in the first time slice (first month)



A correlated with B



25 sites with 60 time slices

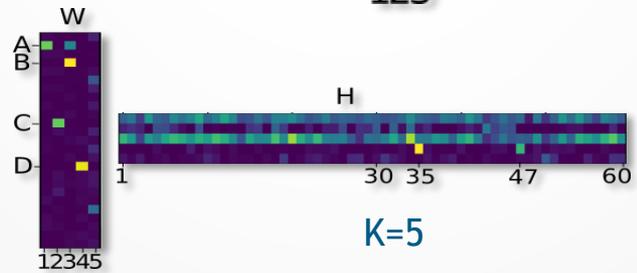
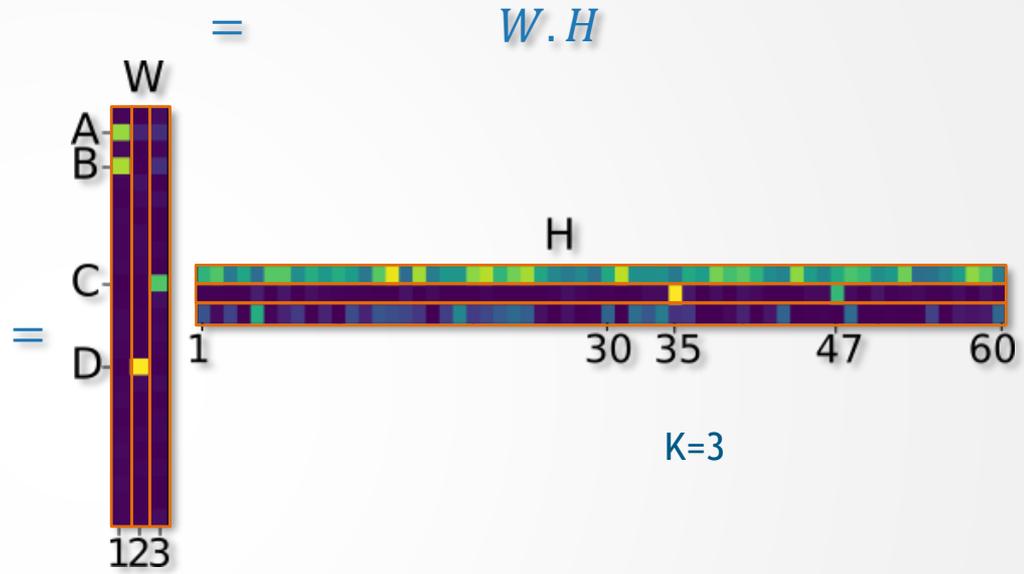
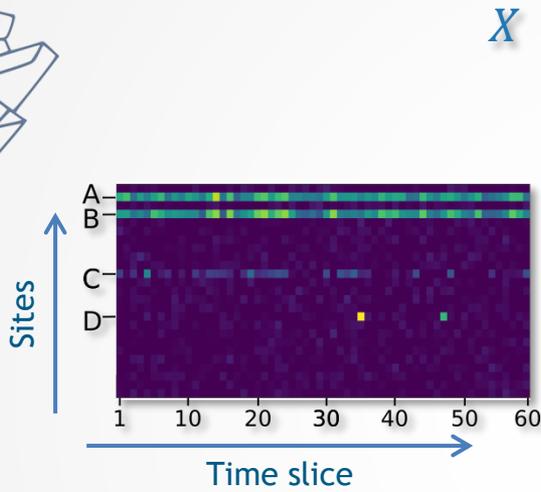
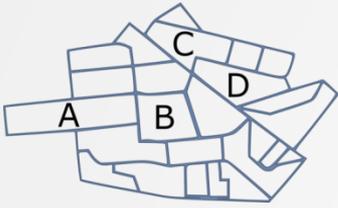
Not large in number, but frequently



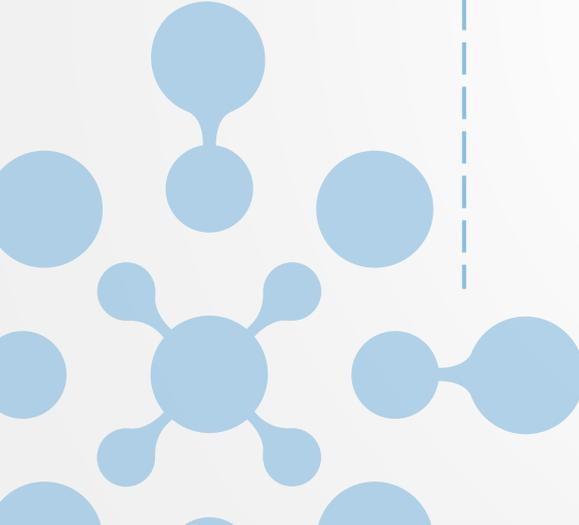
For 35 and 47 (with 15 and 10 crimes).
(Not frequent, but happen in large number in some time slices)



» Data Modelling with NMF



KIM, H.; PARK, H. Sparse non-negative matrix factorizations via alternating non-negativity constrained least squares for microarray data analysis, 2007



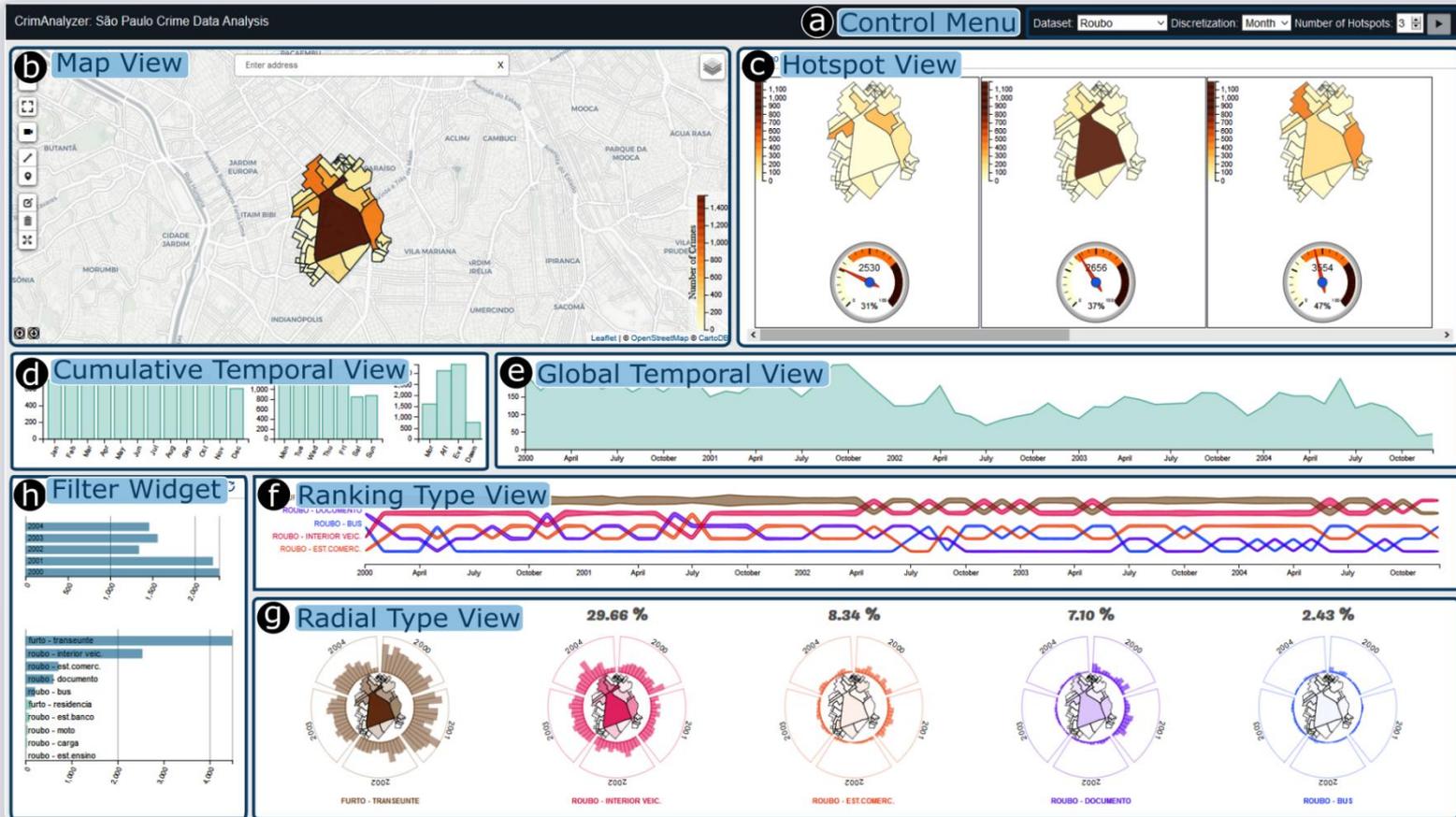
CrimAnalyzer

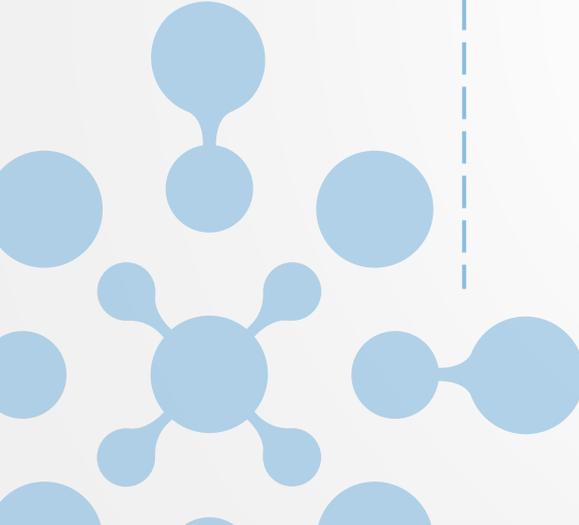
Visual Analytic Tool

» CrimAnalyzer



» CrimAnalyzer

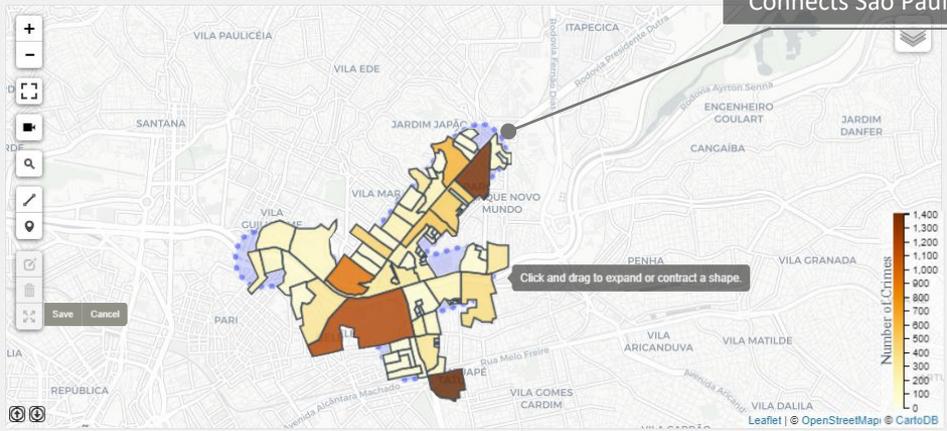




CrimAnalyzer

Case Studies

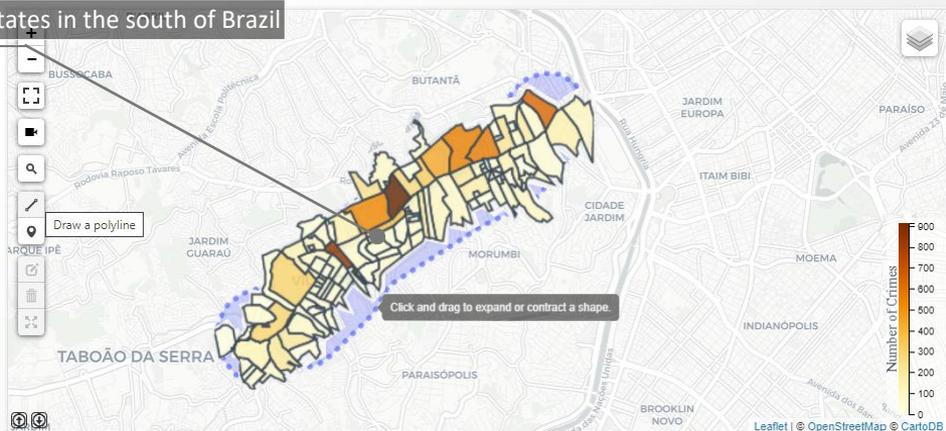
» CrimAnalyzer - Case Study 2



SP230

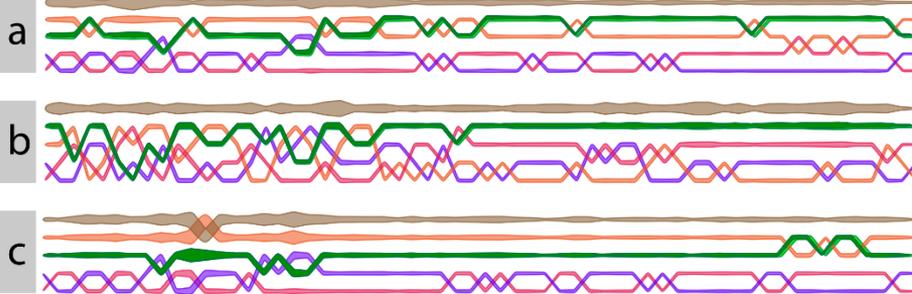
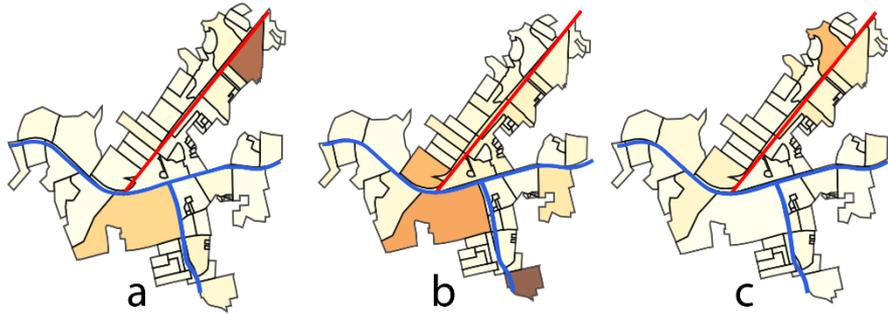
BR116

Connects São Paulo to states in the south of Brazil



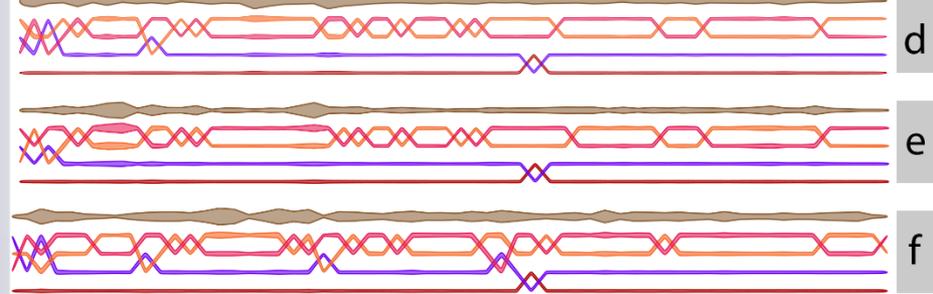
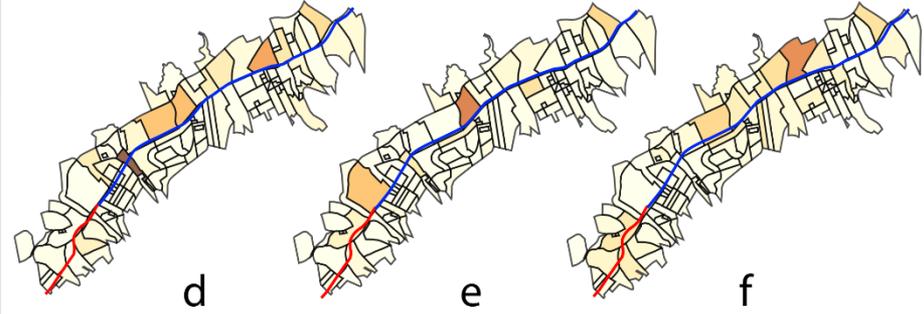
» CrimAnalyzer - Case Study 2

BR116



BR116

SP230



SP230

auto burglary

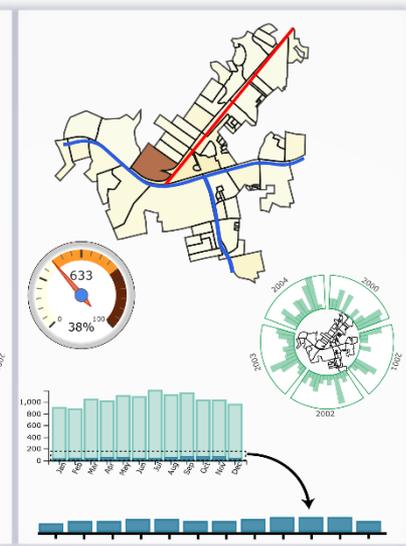
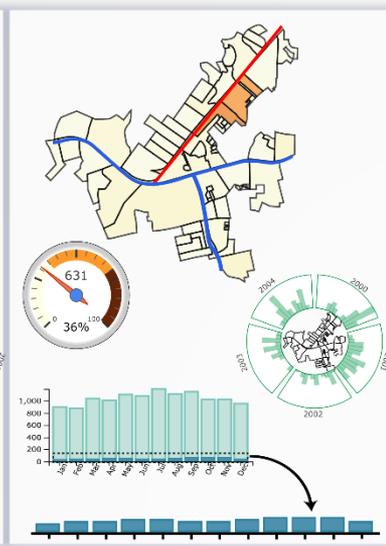
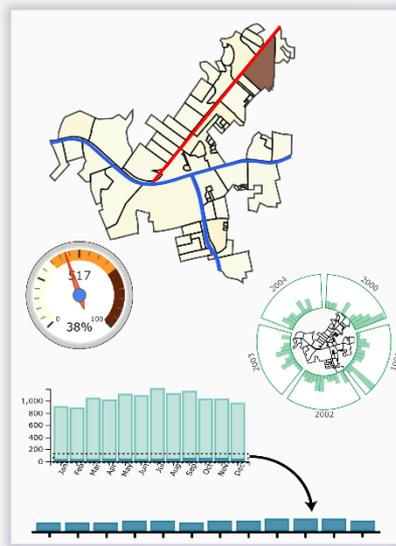
cargo theft

com. place burglary

document theft

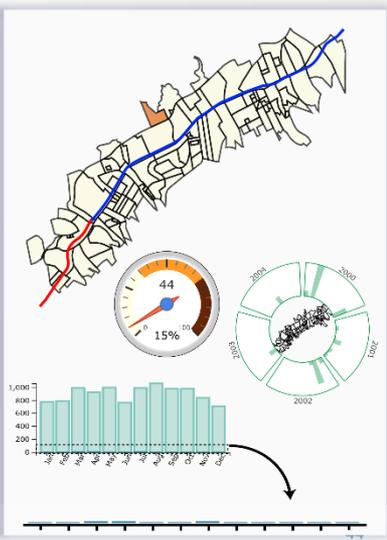
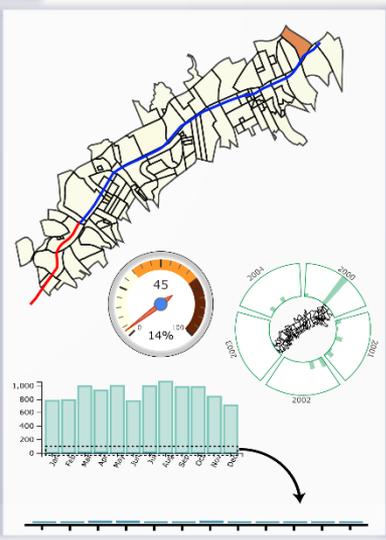
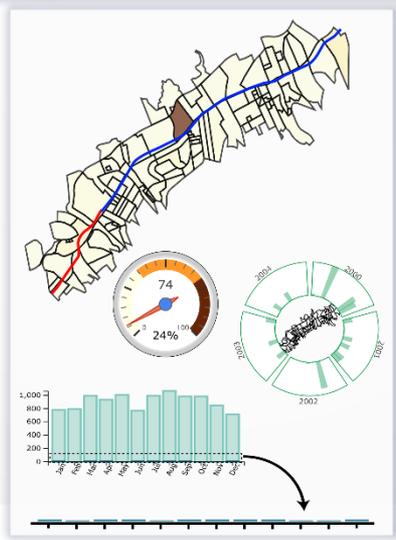
passerby robbery

other



BR116

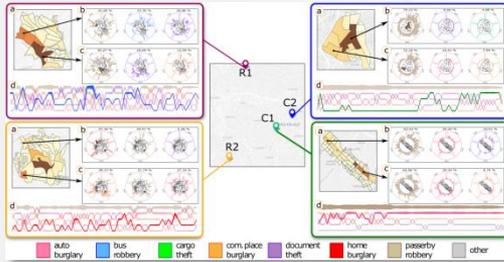
SP230



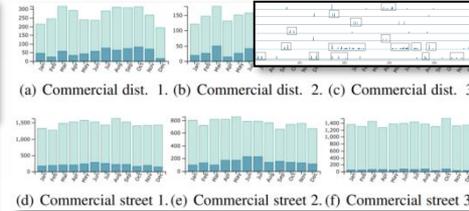
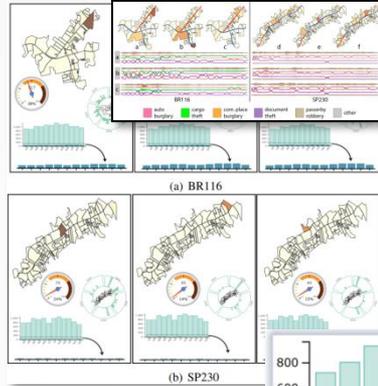
» CrimAnalyzer - Case Studies

Case Studies

Comparing Crime Patterns over the City

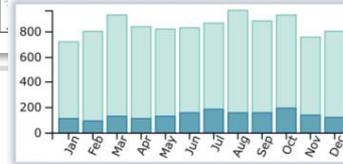


Hotspot Analysis and Cargo Theft

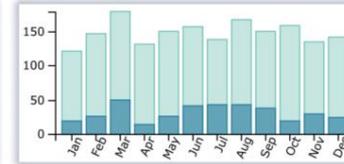


Seasonality and the Temporal Element of Crime

Seasonality [10]



(a) Commercial dist. 1.

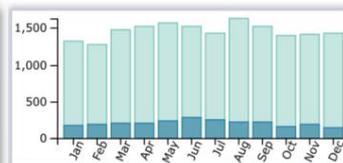
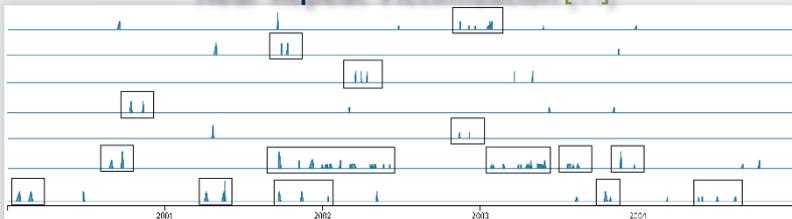


(b) Commercial dist. 2.

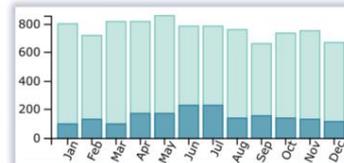


(c) Commercial dist. 3.

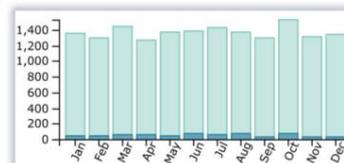
Near Repeat Victimization [11]



(d) Commercial street 1.



(e) Commercial street 2.

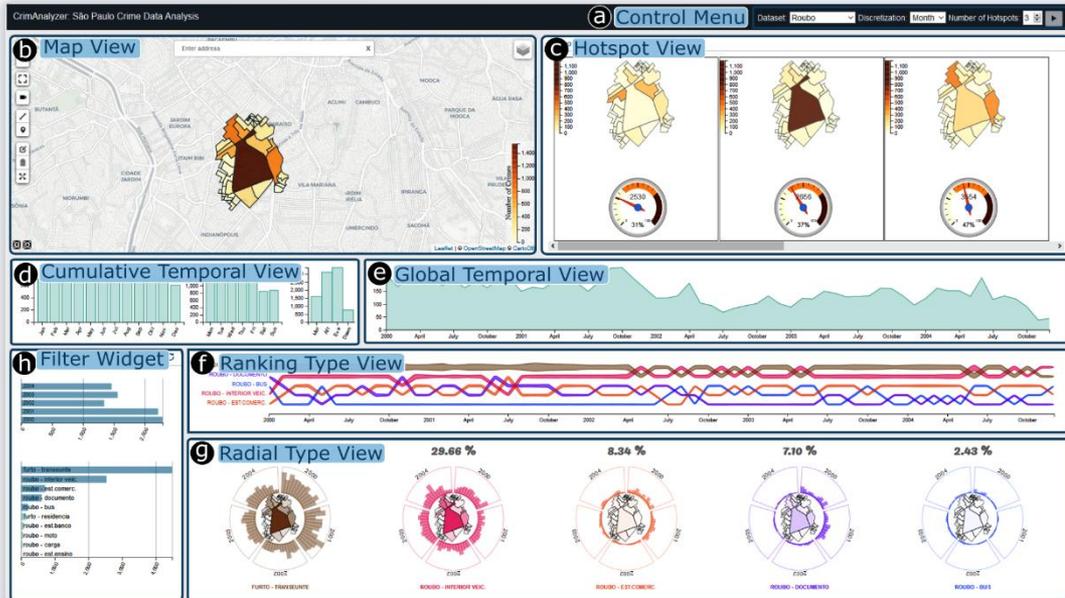


(f) Commercial street 3.

» CrimAnalyzer - Publication

CrimAnalyzer: Understanding Crime Patterns in São Paulo

Published in: [IEEE Transactions on Visualization and Computer Graphics](#)



<https://ieeexplore.ieee.org/document/8869805>

This article has been accepted for publication in a journal that has been indexed by the IEEE Crossref database. For more information, see the IEEE Crossref database at <http://ieeexplore.ieee.org>. The final version of this article is available at <http://dx.doi.org/10.1109/TVCG.2019.2947975>.

JOURNAL OF VEC CLASS FILES, VOL. 14, NO. 8, AUGUST 2015

CrimAnalyzer: Understanding Crime Patterns in São Paulo

Germain Garcia, Jaqueline Silveira, Jorge Poco *Member, IEEE*, Afonso Paiva, Marcelo Batista Nery, Claudio T. Silva *Fellow, IEEE*, Sergio Adorno, Luis Gustavo Nonato *Member, IEEE*

Abstract—São Paulo is the largest city in South America, with crime rates that reflect its size. The number and type of crimes vary considerably around the city, assuming different patterns depending on urban and social characteristics of each particular location. Previous works have mostly focused on the analysis of crimes with the intent of uncovering patterns associated to social factors, seasonality, and urban routine activities. Therefore, those studies and tools are more global in the sense that they are not designed to investigate specific regions of the city such as particular neighborhoods, avenues, or public areas. Tools able to explore specific locations of the city are essential for domain experts to accomplish their analysis in a bottom-up fashion. Revealing how urban features related to mobility, passenger behavior, and presence of public infrastructures (e.g., terminals of public transportation and schools) can influence the quantity and type of crimes. In this paper, we present CrimAnalyzer, a visual analytic tool that allows users to study the behavior of crimes in specific regions of a city. The system allows users to identify local hotspots and the pattern of crimes associated to them, while still showing how hotspots and corresponding crime patterns change over time. CrimAnalyzer has been developed from the needs of a team of experts in criminology and deals with three major challenges: i) flexibility to explore local regions and understand their crime patterns, ii) identification of spatial crime hotspots that might not be the most prevalent ones in terms of the number of crimes but that are important enough to be investigated, and iii) understand the dynamic of crime patterns over time. The effectiveness and usefulness of the proposed system are demonstrated by qualitative and quantitative comparisons as well as by case studies run by domain experts involving real data. The experiments show the capability of CrimAnalyzer in identifying crime-related phenomena.

Index Terms—Crime Data, Spatio-Temporal Data, Visual Analytics, Non-Negative Matrix Factorization

1 INTRODUCTION

SINCE the mid-transition process with this political it increasingly be solv has not happened. In an explosion of cor crimes. There is still the reasons that en; and violence in Brau

Among the explanations that arise more frequently is the exhaustion of traditional security policy models. Concerning this last aspect, it is undeniable that crimes have not only grown, but also become more violent and modernized. In contrast, agencies in charge of law and order (e.g. police and criminal justice systems) have not kept up with these trends. The gap between the dynamics of crime and violence and the state's ability to contain them within the rule of law has widened. Therefore, introducing modern instruments for the management of public order and crime containment is imperative to make public security policies more efficient, not

IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS

under-development

information Systems behavior of crimes, criminologists in their local geography as hich they occur in a ring and visualizing se-related attributes

to reveal particular information such as burglary in commercial areas or the seasonality of auto theft in certain neighborhoods is among the key components of a crime mapping approach [38]. Most existing tools developed for crime mapping focused on the detection of hotspots, that is, areas with a high number of criminal incidents [14]. Although sophisticated mechanisms have been proposed to detect hotspots [15], the search for a high prevalence of crimes tends to neglecting sites where certain types of crimes are frequent but not sufficiently intense to be considered statistically significant [51]. Moreover, most techniques enable only rudimentary mechanisms to analyze an important component of unlawful activities, the temporal evolution of crimes and their patterns. In fact, visualization resources for temporal analysis available in the majority of crime mapping systems are very restrictive, impairing users from performing elaborated queries and data exploration [3].

There is yet another important aspect to be considered in the context of crime mapping, the specificities of urban areas under analysis. São Paulo, for example, bears one of the highest crime

- Germain Garcia, Jaqueline Silveira, and Afonso Paiva are with ICMC-USP, São Carlos, Brazil. E-mail: {germaingarcia,alvo,jaque}@usp.br
- Marcelo Batista Nery is with BIOC-FAPESP and Institute of Advanced Studies - Global Cities@usp.br. E-mail: mbnery@gmail.com
- Sergio Adorno is with NEV-USP, São Paulo, Brazil. E-mail: maradorno@usp.br
- Jorge Poco is with Fundação Getúlio Vargas, Brazil and Universidad Católica San Pablo. E-mail: jorge.poco@fgv.br
- Claudio Silva is with New York University, USA. E-mail: csilva@nyu.edu
- Luis Gustavo Nonato is with ICMC-USP, São Carlos, Brazil and New York University, USA. E-mail: gnonato@icmc.usp.br

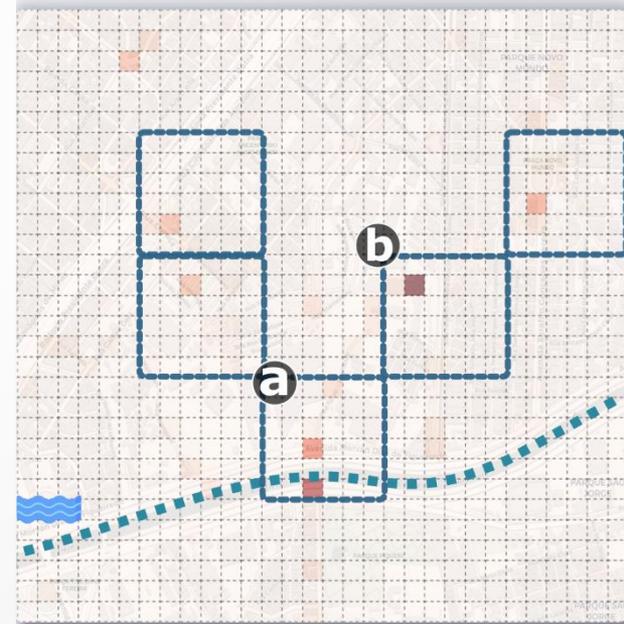
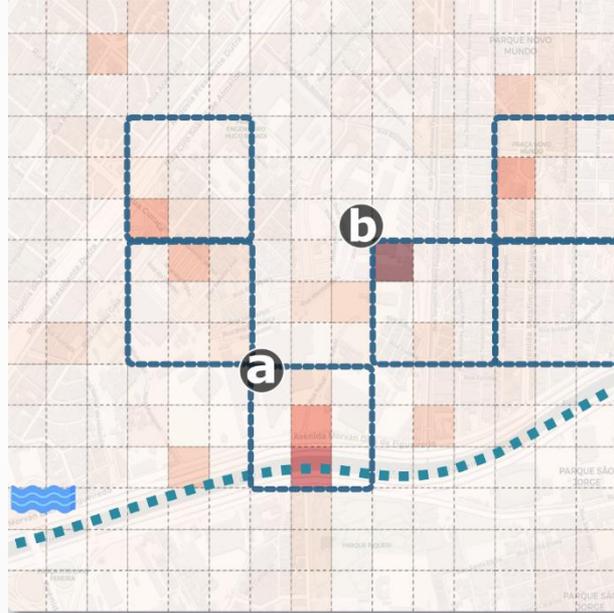
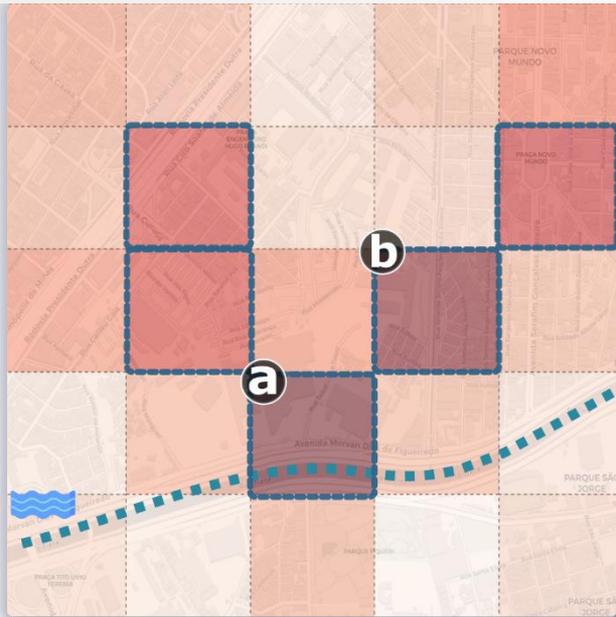
There is yet another important aspect to be considered in the context of crime mapping, the specificities of urban areas under analysis. São Paulo, for example, bears one of the highest crime

1. São Paulo is both a state and a city. In this paper, any time that we do not explicitly specify, São Paulo will refer to the city.



Mirante

» Mirante - Motivation

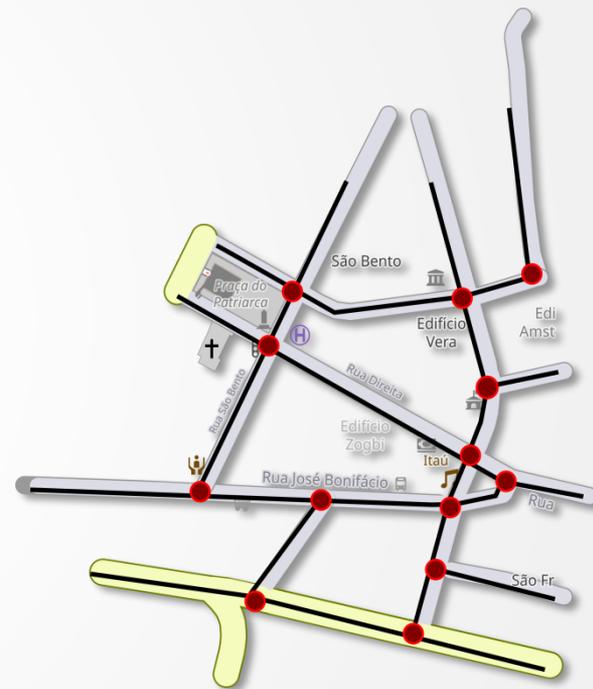
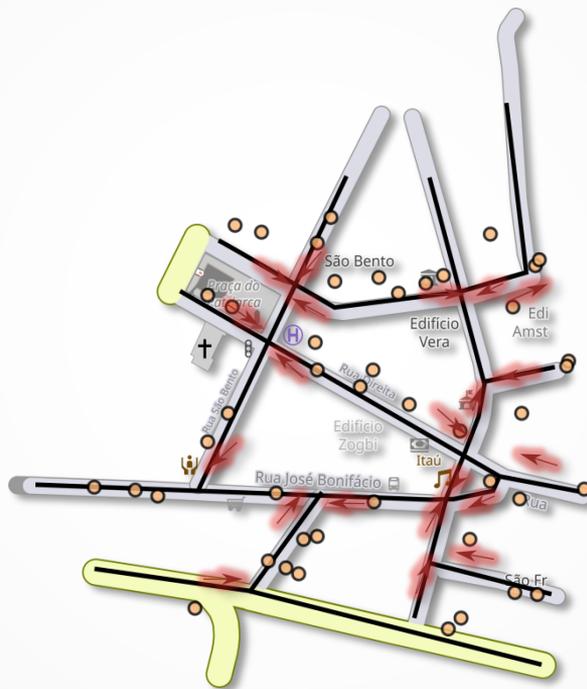
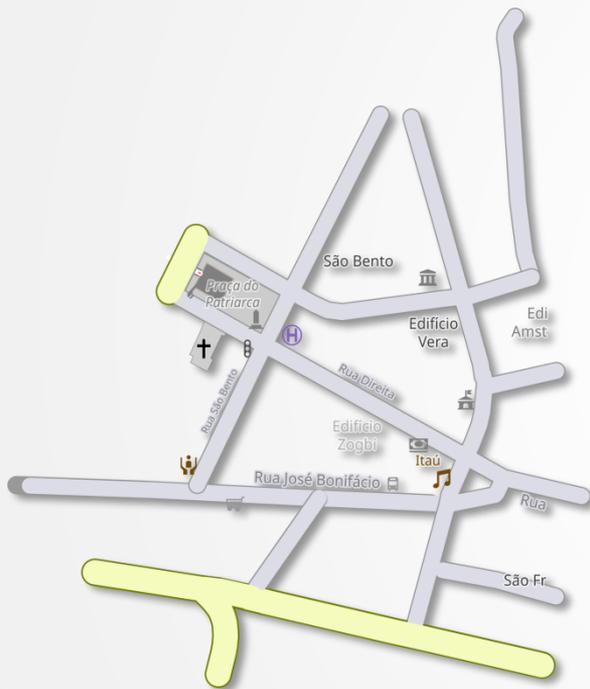




Mirante

Data Modeling

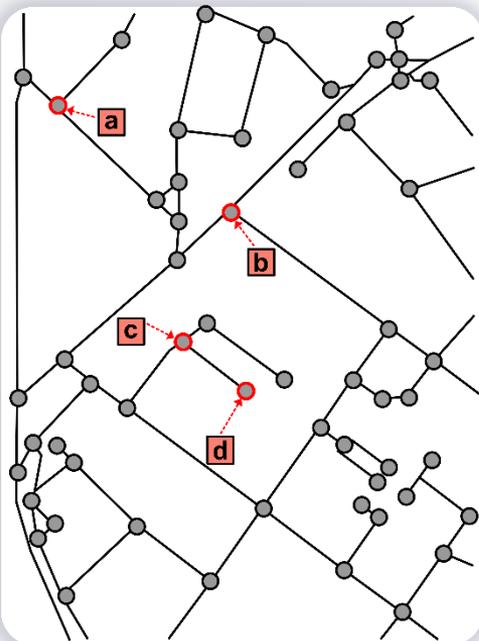
» Mirante - Data Modeling



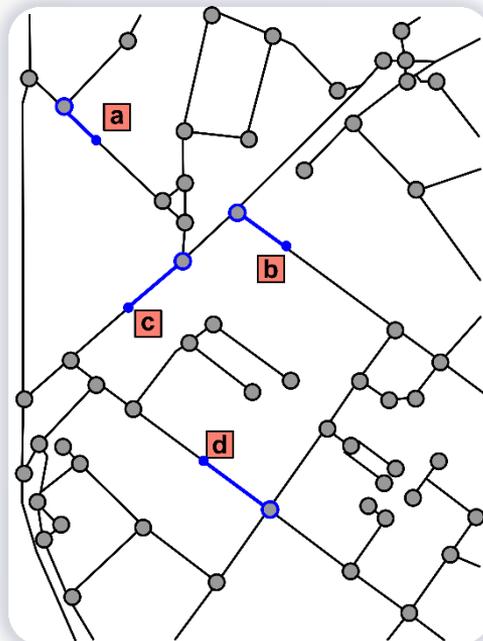
» Mirante - Algorithm

$$L_{crime} = \{c_0, c_1, \dots, c_n\}$$

$$G = (V, E)$$



Closest node strategy



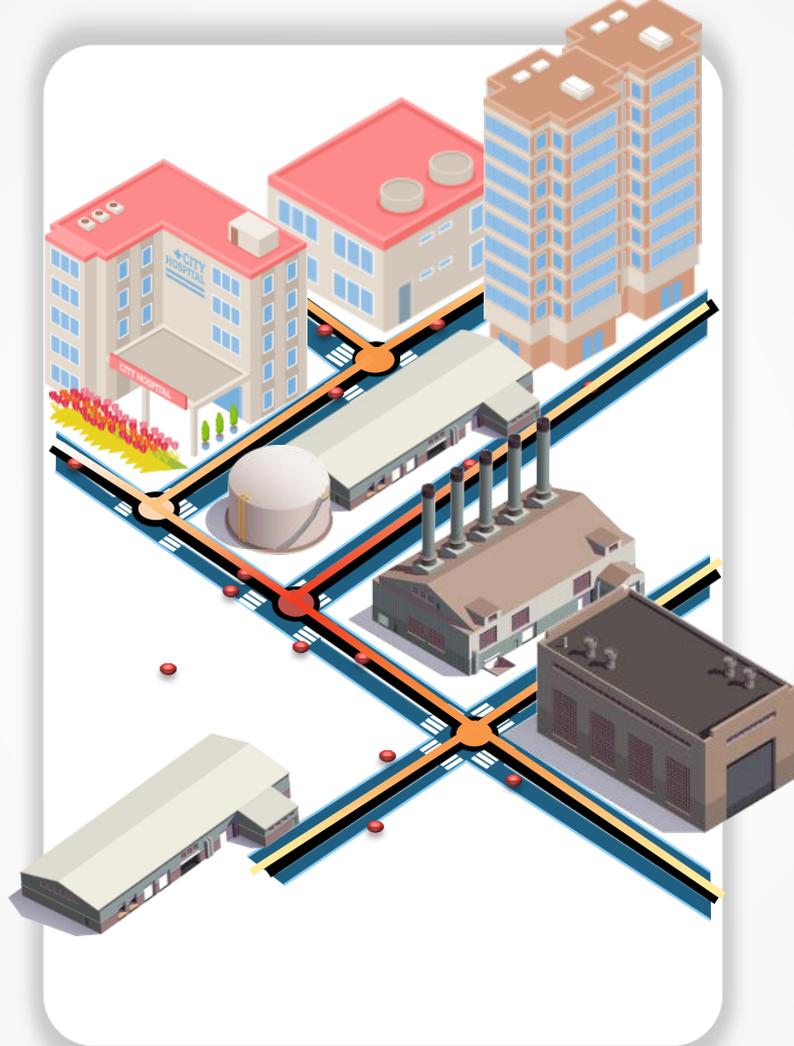
Edge-node strategy

Algorithm 1 – Assigning crimes to vertices.

Input: Graph G , List L_{crime}

Output: Graph G

- 1: $v_i.crimines \leftarrow []$, $\forall v_i \in G.vertices$
- 2: **for** $i \leftarrow 1$ **To** $length(L_{crime})$ **do**
- 3: $c_{curr} \leftarrow L_{crime}[i]$
- 4: $e_{near} \leftarrow G.get_nearest_edge(c_{curr})$
- 5: $(v_1, v_2) \leftarrow G.get_vertices(e_{near})$
- 6: $d_1 \leftarrow greatCircleDistance(c_{curr}, v_1)$
- 7: $d_2 \leftarrow greatCircleDistance(c_{curr}, v_2)$
- 8: **if** $d_1 < d_2$ **then**
- 9: $v_1.crimines.append(c_{curr})$
- 10: **else**
- 11: $v_2.crimines.append(c_{curr})$
- 12: **end if**
- 13: **end for**





Closest Node Strategy **X**



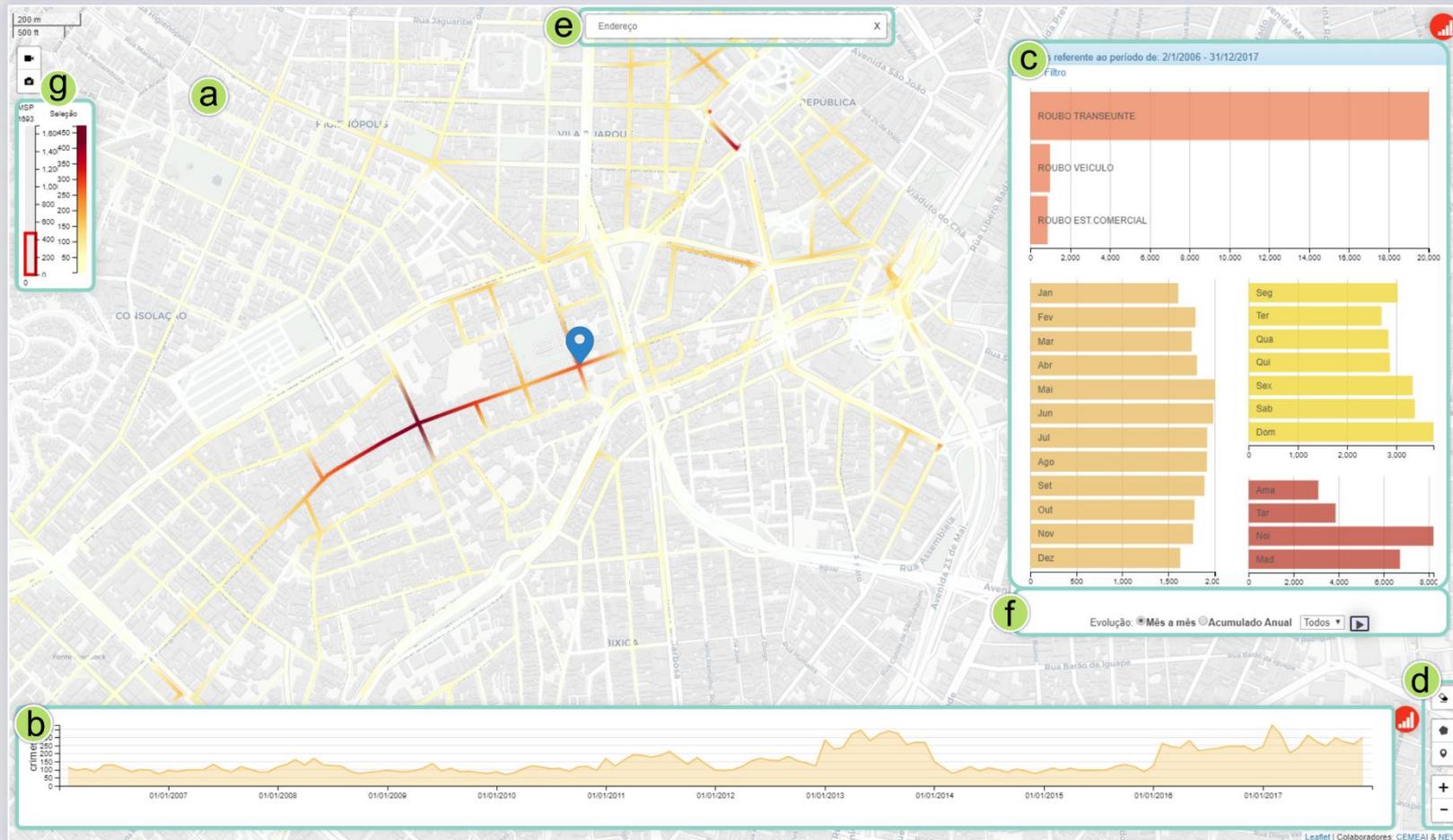
Edge-Node Strategy **✓**



Mirante

Visualization Tool

Mirante





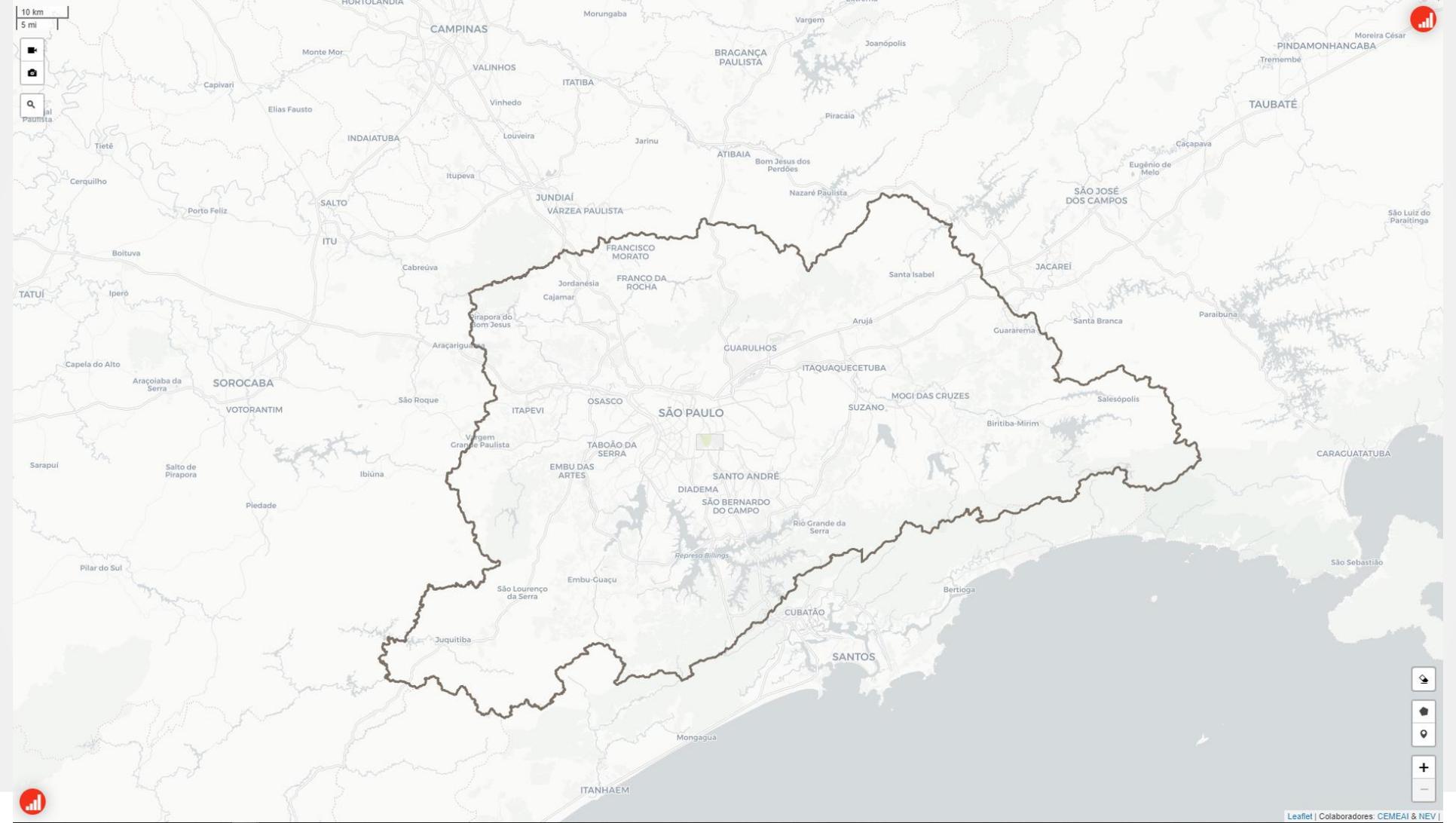
Mirante

Case Studies



Case Study 1

Vehicle Robbery in São Paulo



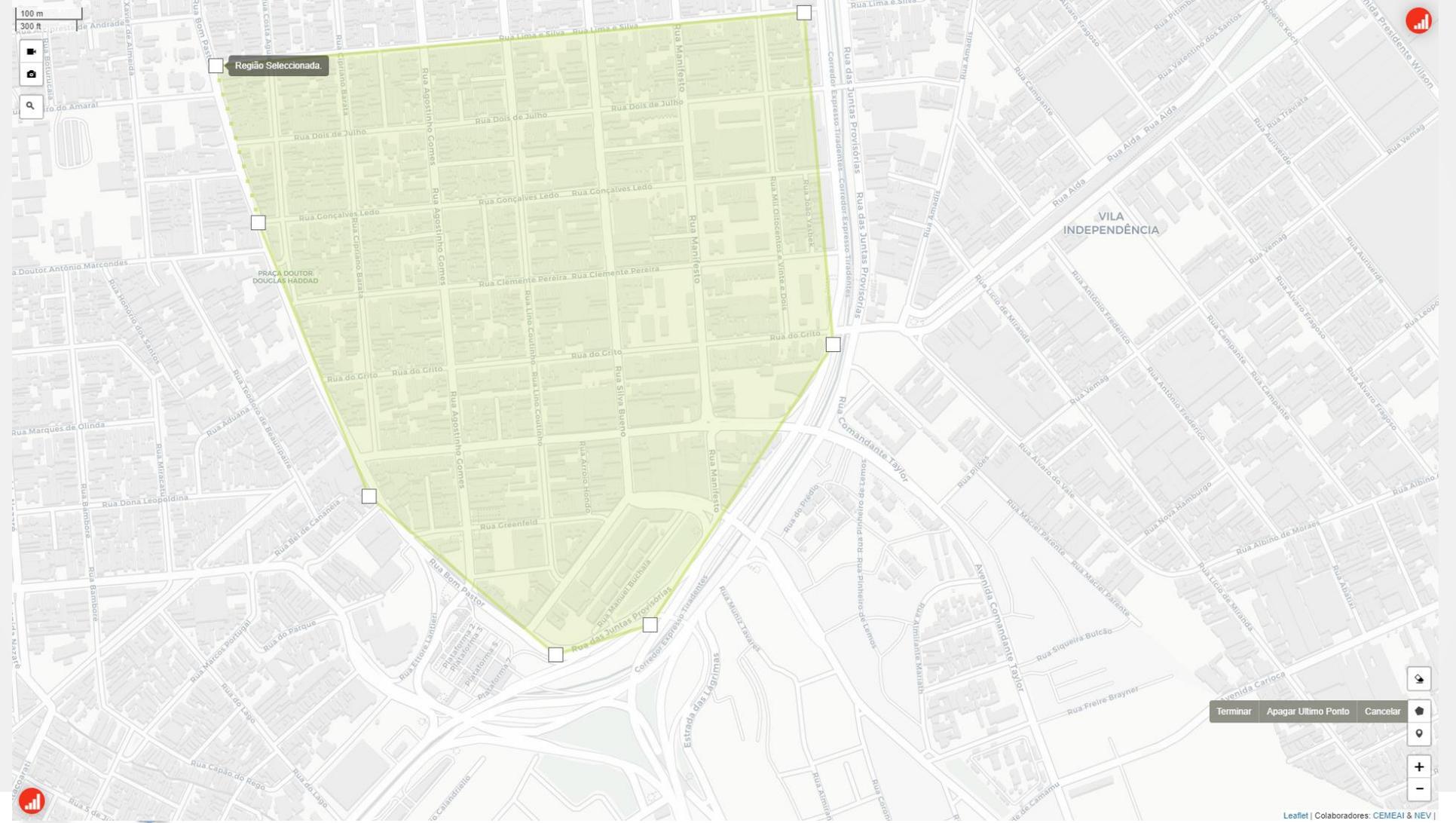
10 km

5 mi



São Paulo





100 m

300 ft



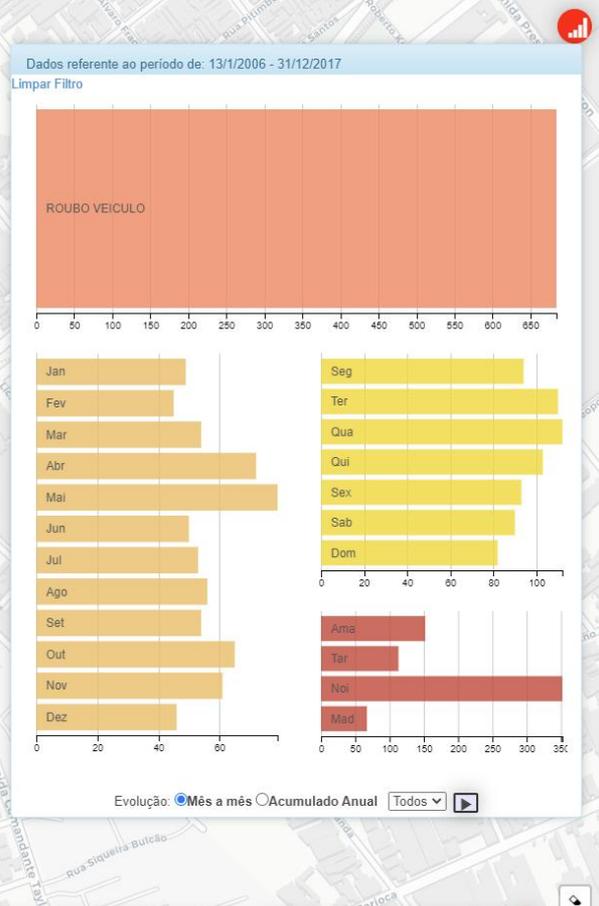
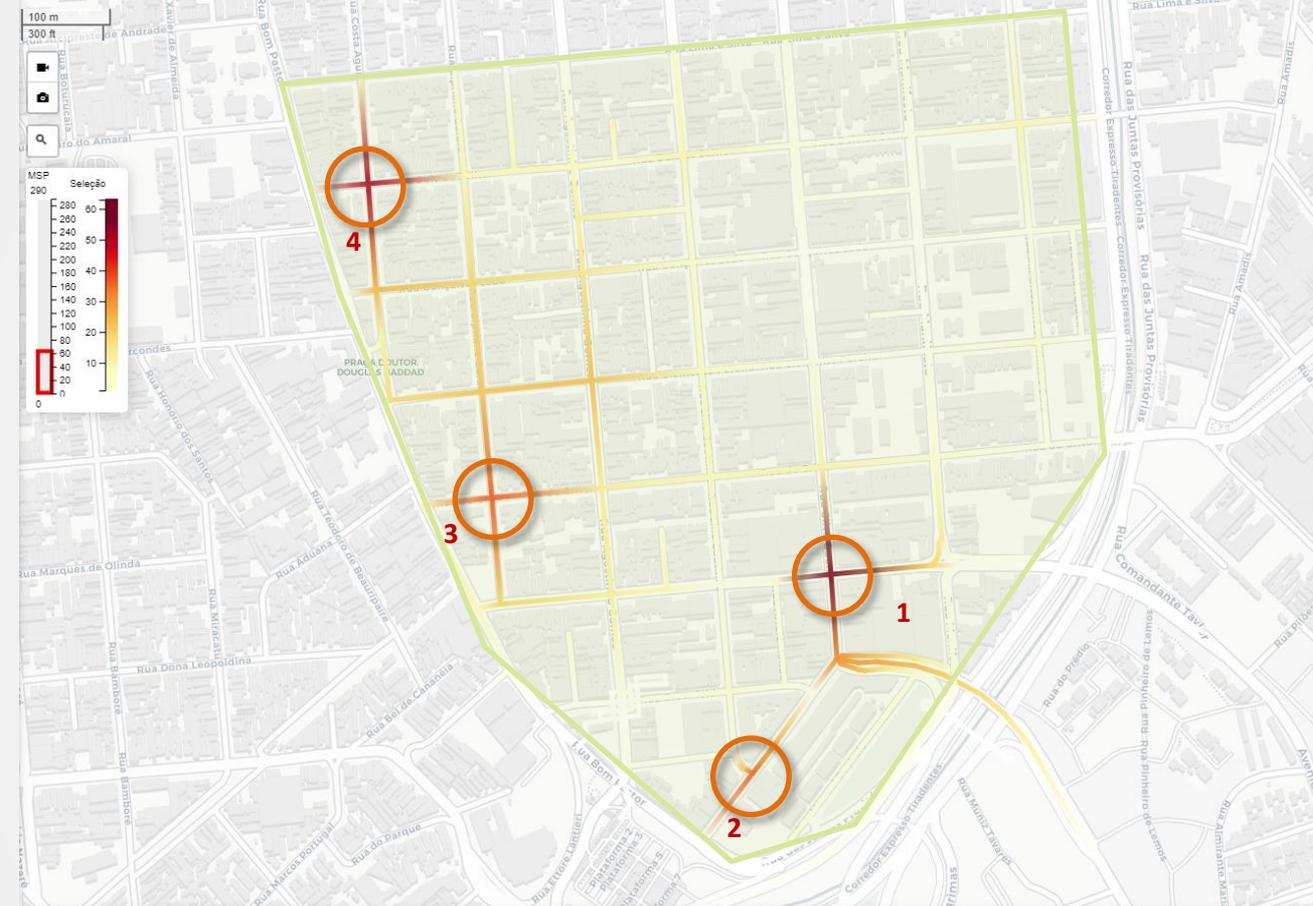
Região Seleccionada.

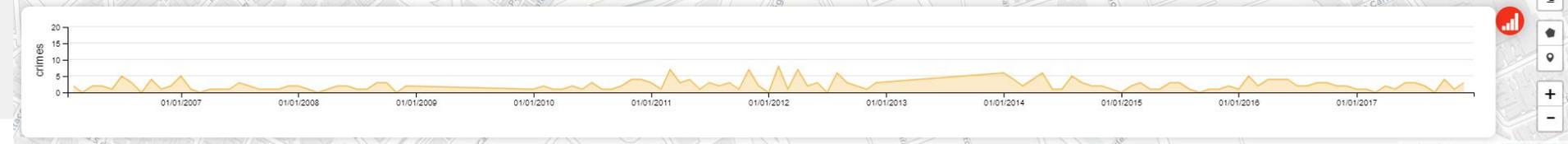
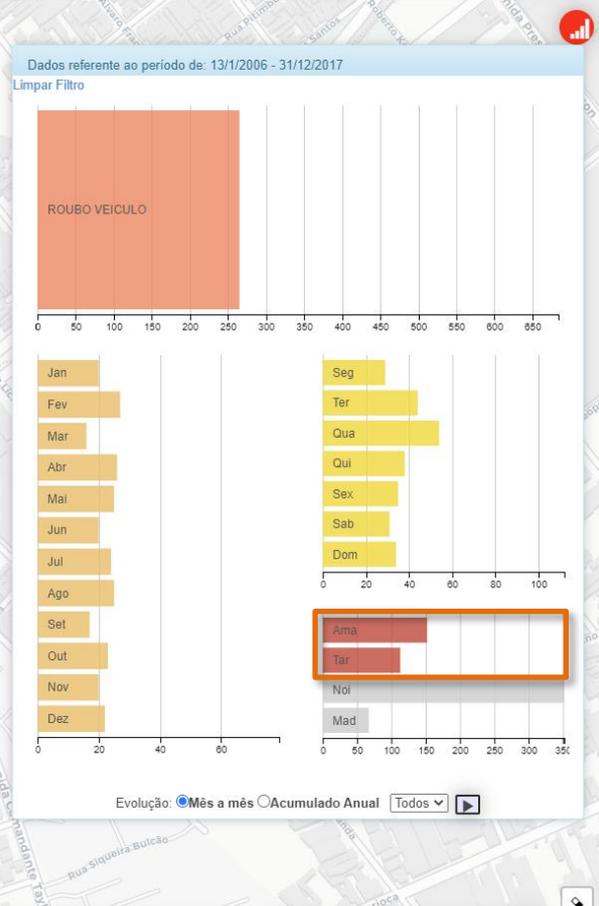
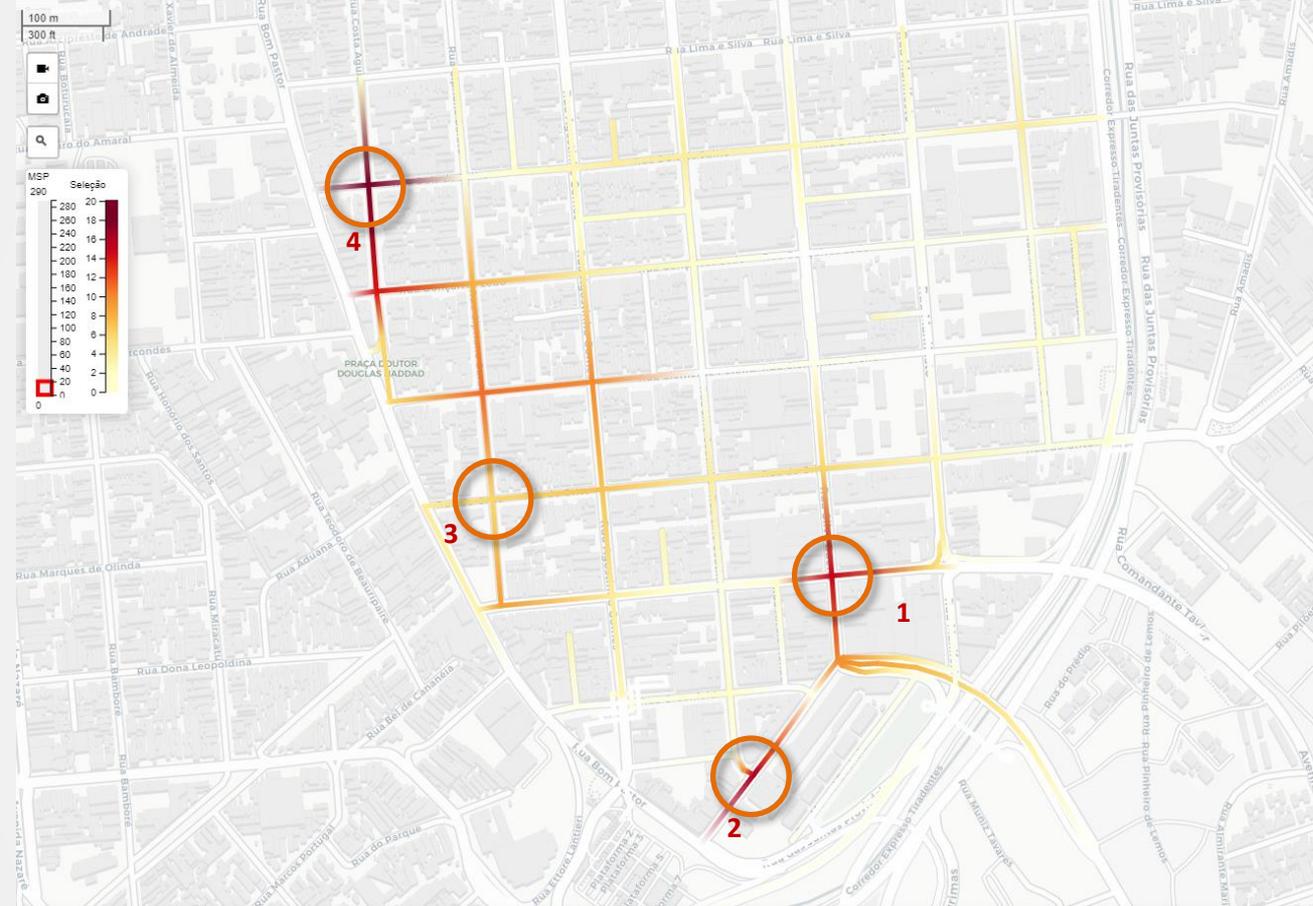
PRAÇA DOUTOR DOUGLAS HADDAD

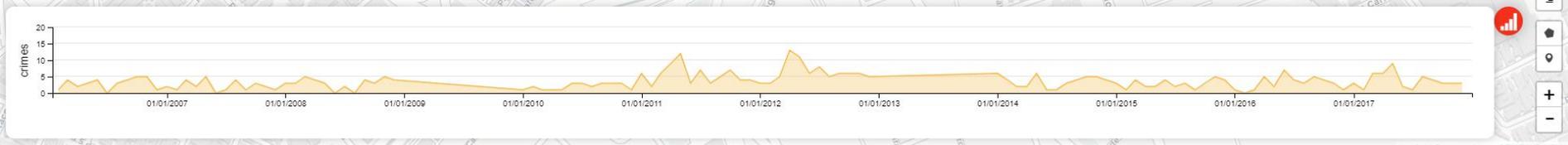
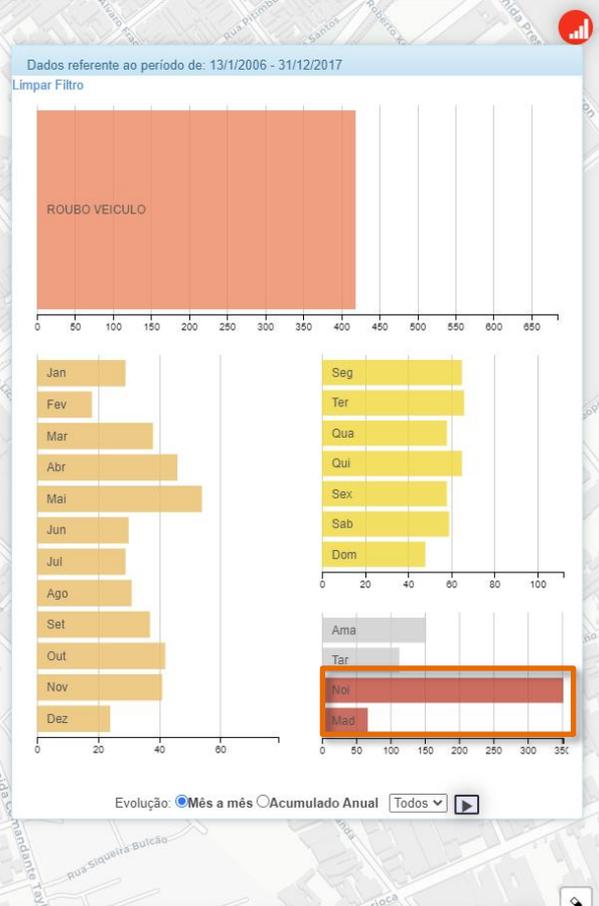
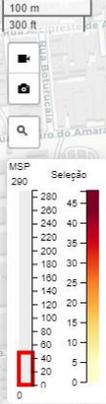
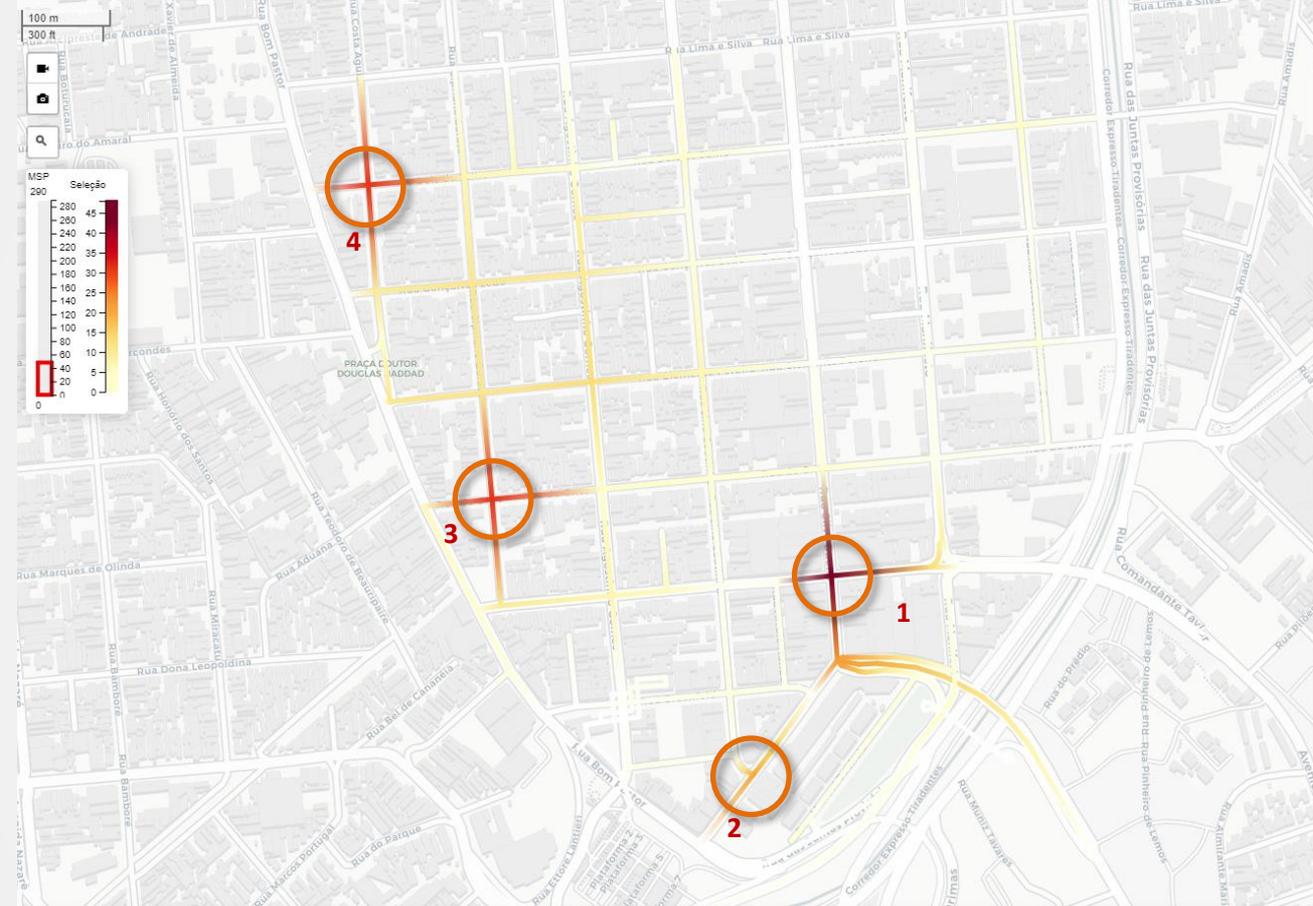
VILA INDEPENDÊNCIA

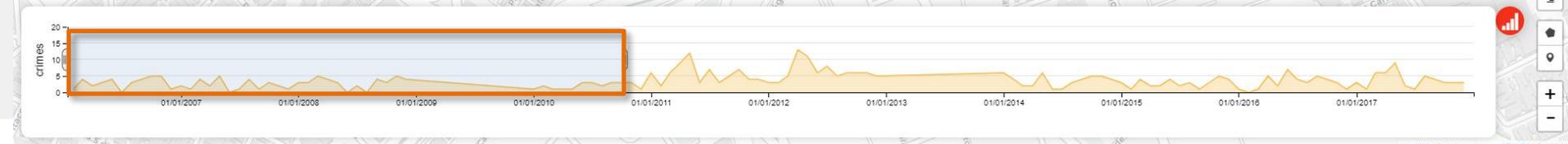
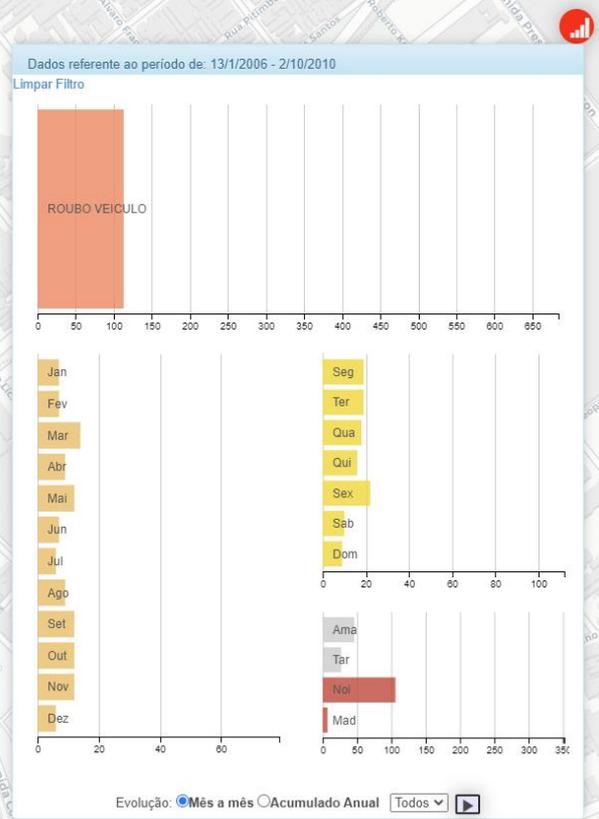
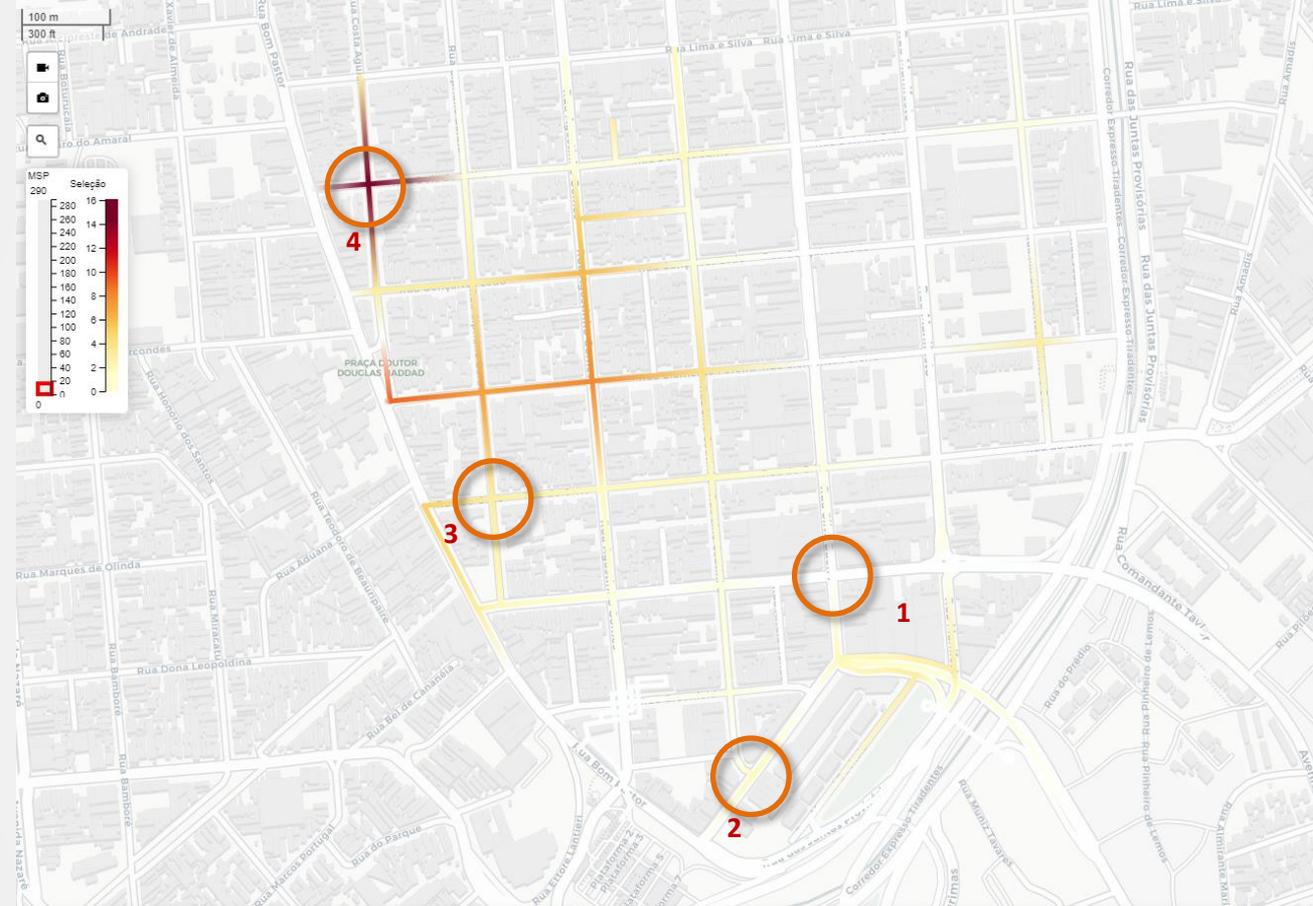
Terminar Apagar Último Ponto Cancelar

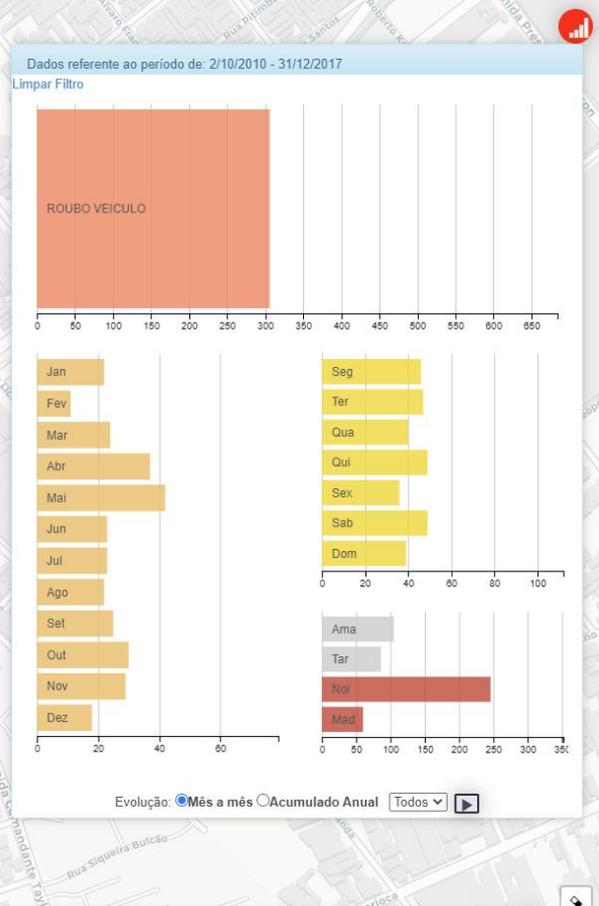
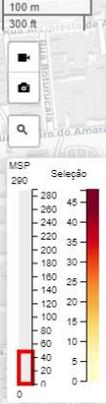
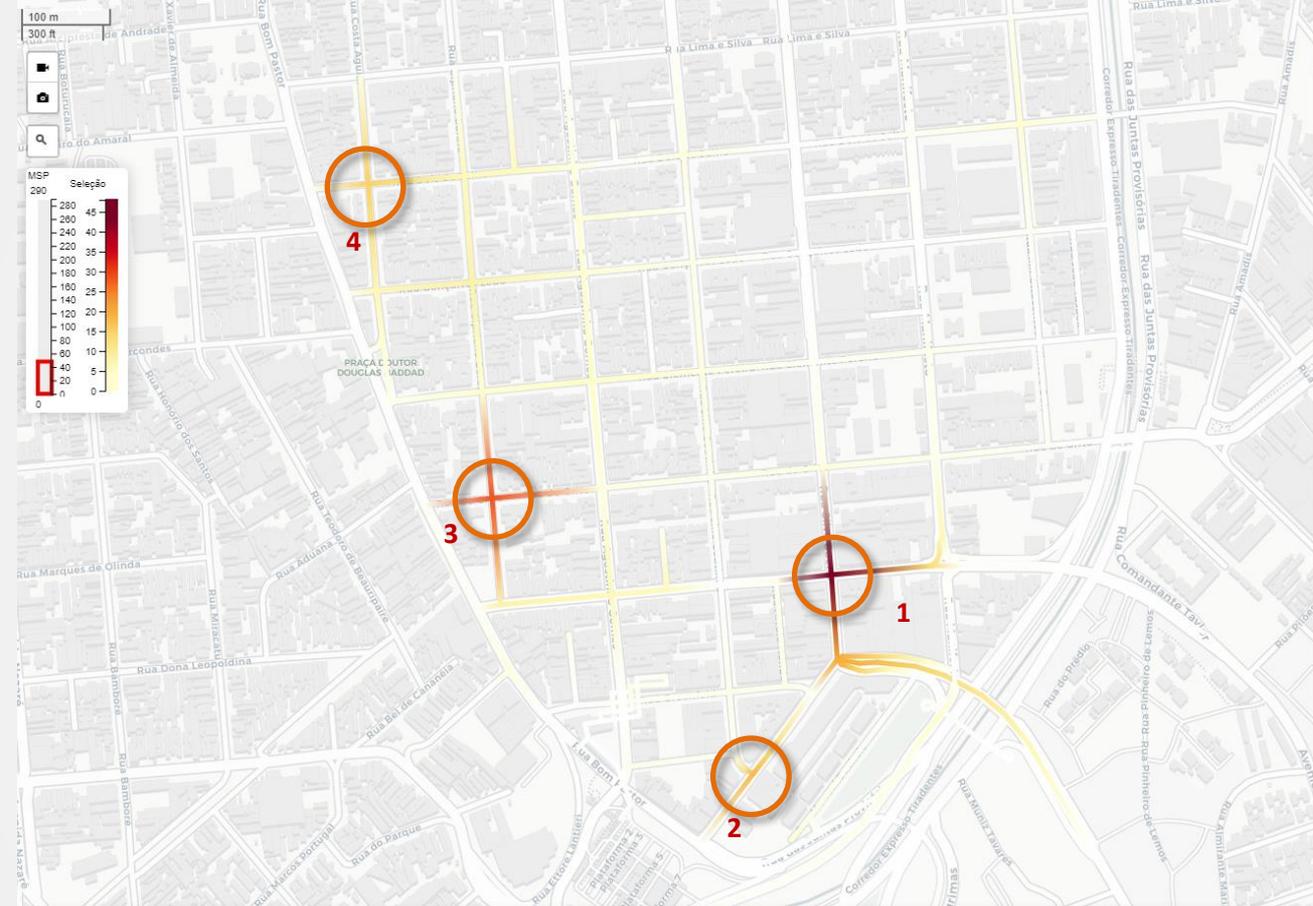










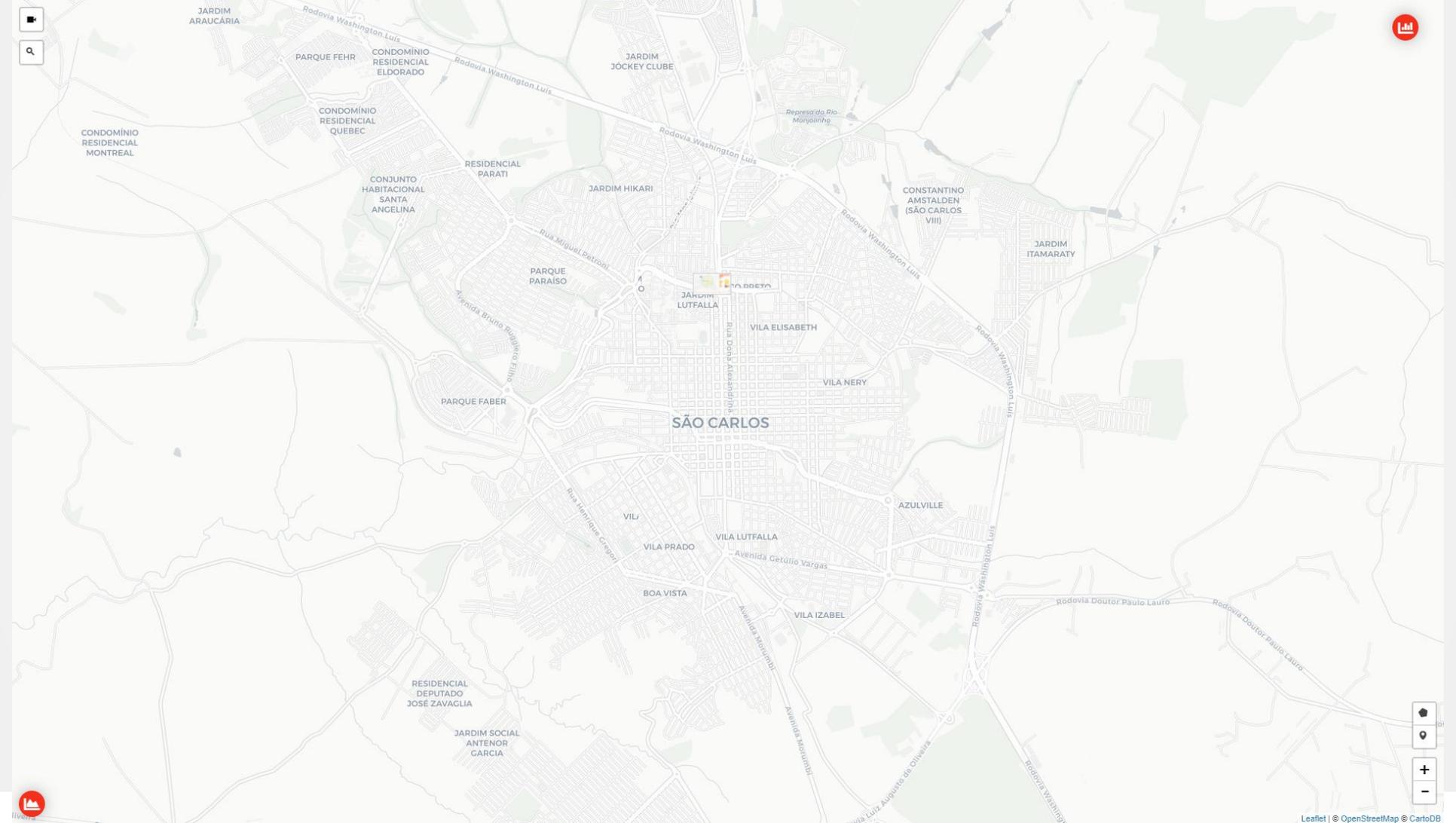






Case Study 2

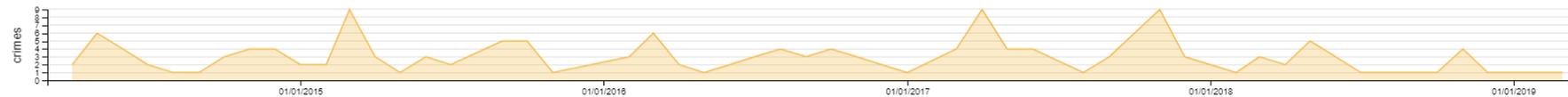
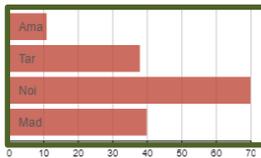
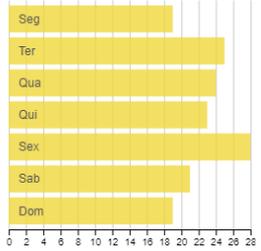
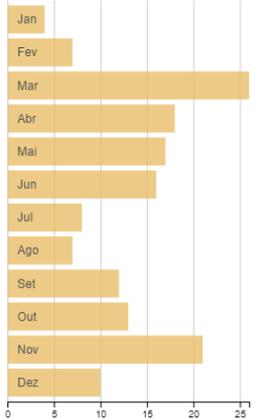
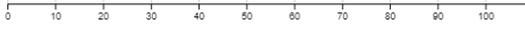
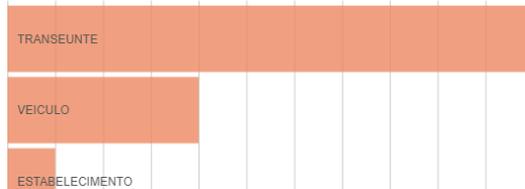
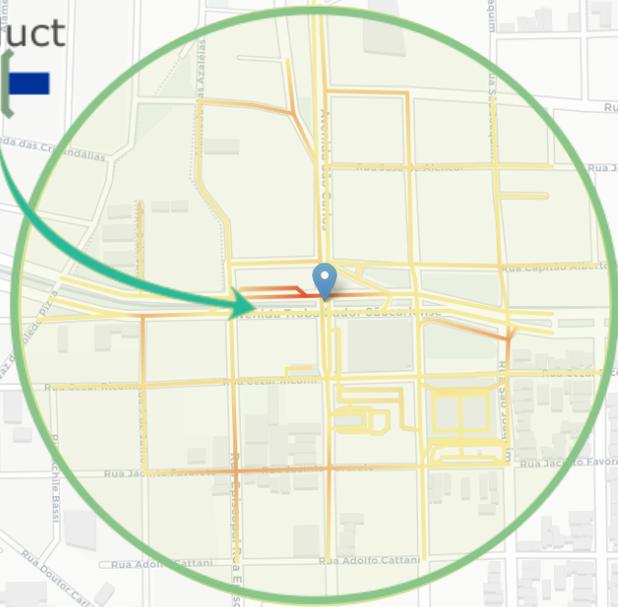
Passerby Robbery in São Carlos



SÃO CARLOS

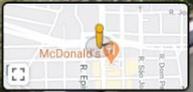


Viaduct





285 Av. Trab. São Carlos
 São Carlos, Estado de São Paulo
 Google
 Street View



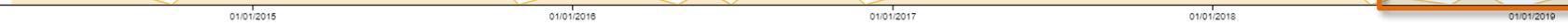
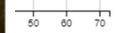
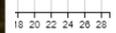
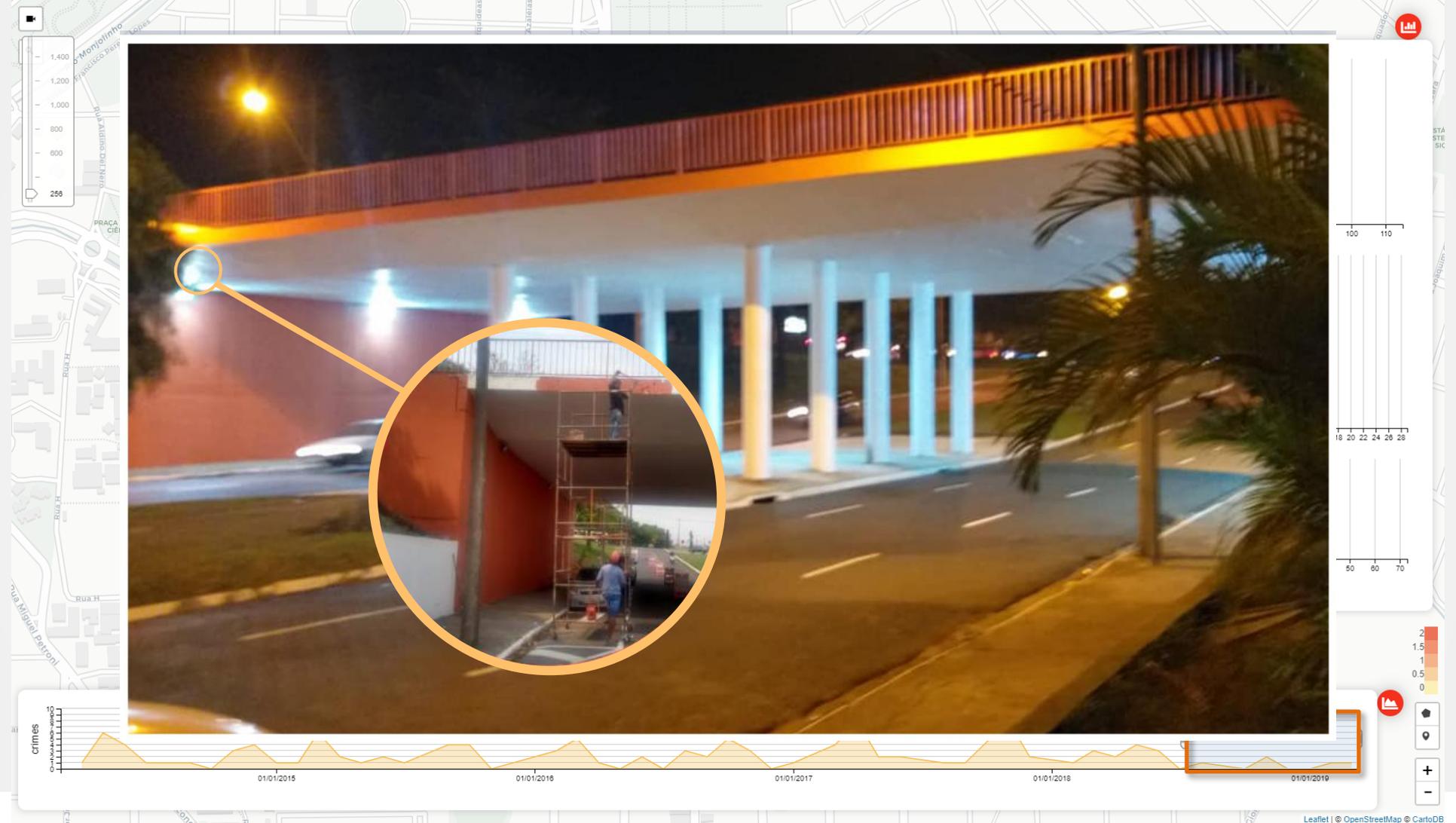


338 Av. Trab. São Carlesse
São Carlos, Estado de São Paulo
Google
Street View



4
3
2
1
0
Home Location + -

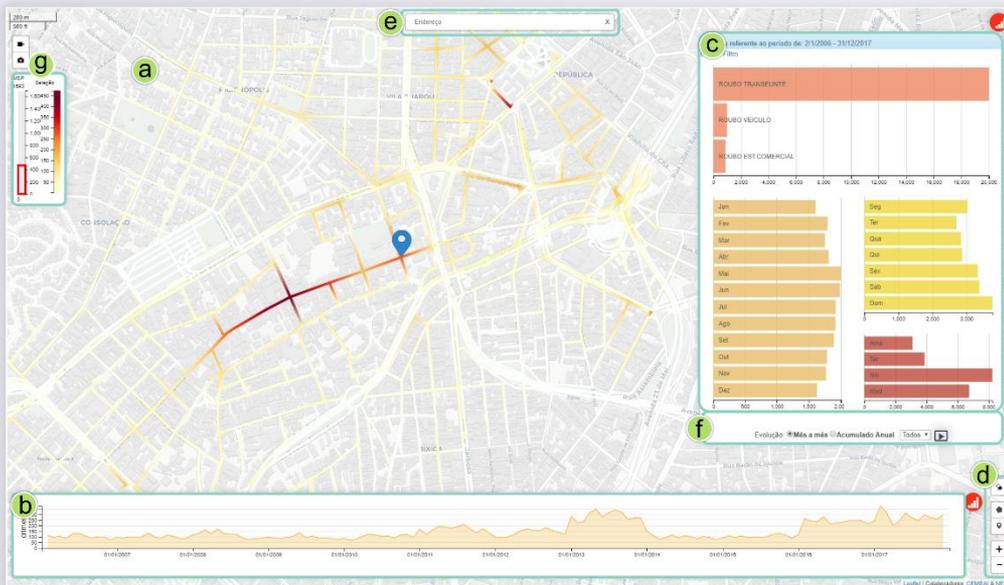




» Mirante - Publication

Mirante: A visualization tool for analyzing urban crimes

Published in: 33rd Conference on Graphics, Patterns and Images



<https://ieeexplore.ieee.org/abstract/document/9265984>

Mirante: A visualization tool for analyzing urban crimes

Germain Garcia-Zanabria, Erick Gomez-Nieto
Jaqueline Silveira
Universidade de São Paulo
{germaingarcia, erick.gomez, alva.jaque}@usp.br

Jorge Poco
Fundação Getúlio Vargas
jorge.poco@fgv.br

Marcelo Nery, Sergio Adorno,
Luís G. Nonato
Universidade de São Paulo
mbery@gmail.com, sado@usp.br,
gsonato@icmc.usp.br

Abstract—Visualization assisted crime analysis tools used by public security agencies are usually designed to explore large urban areas, relying on grid-based heatmaps to reveal spatial crime distribution in whole districts, regions, and neighborhoods. Therefore, those tools can hardly identify micro-scale patterns closely related to crime opportunity, whose understanding is fundamental to the planning of preventive actions. Enabling a combined analysis of spatial patterns and their evolution over time is another challenge faced by most crime analysis tools. In this paper, we present *Mirante*, a crime mapping visualization system that allows spatiotemporal analysis of crime patterns in a street-level scale. In contrast to conventional tools, *Mirante* builds upon street-level heatmaps and other visualization resources that enable spatial and temporal pattern analysis over time. *Mirante* allows domain experts, versatile to be in demonstrate the run by domain different character were capable of of the cities with certain types of

data aggregated on grid cells, each covering hundreds of square meters. However, recent studies point out the importance of analyzing micro places [13]–[16], as crime rarely concentrates on regions larger than a street segment or corner. In fact, several researchers have shown that crimes mostly occur near specific locations such as bars, fast-food restaurants, check-cashing centers, and pawnshops, since those places attract distracted and vulnerable people who carry money and valuables [14], [17]. In other words, the environment of those places creates a crime opportunity. Therefore, relying on spatial discretizations such as the regular grids renders fine-grained crime analysis a non-trivial task, since the identification of micro places is not so straightforward. A cell containing a street segment, grid resolution is not fine enough, hampering the identification of possible causes. The analysis of crime patterns at a street-level scale, suppose that a crime occurs during a street corner. In a grid representation, such a temporal behavior can hardly be caught if both corners lie on the same grid cell.

Understanding the problem due to the interplay between the spatial and temporal dynamics of crimes, the large variability of patterns among the different types of crimes, and the large amount of data involved in such analysis. In this context, the branch of Geographic Information Systems (GIS) called *Crime Mapping* focuses on developing tools to explore and analyze the spatio-temporal behavior of crimes, leveraging the importance of local urban, social, and environmental characteristics as determinants for crime opportunity [1], [2]. Current crime mapping tools combine techniques from different fields such as mathematics and statistics [3]–[5], machine learning [6], [7], optimization and visualization [8]–[10], and social sciences [11], [12]. Examples of crime mapping systems implemented to increase transparency for the population and to support agencies in charge of public security are *LexisNexis*¹, *NYC Crime Map*², *CitZenRIMS*³, and *CrimeMapping*⁴.

An important aspect of crime mapping is the spatial discretization. Most techniques rely on regular grids with crime

representation, such a temporal behavior can hardly be caught if both corners lie on the same grid cell. In collaboration with domain experts, we designed *Mirante*, a scalable and versatile visualization tool tailored to explore crime data in a street-level of detail. Considering street corners as nodes and street segments as edges, *Mirante* assumes city street maps as the spatial discretization. Crime data is spatially aggregated on street corners using an *edge-node* strategy rather than Euclidean distance, which avoids several issues present in grid cell aggregation. *Mirante* provides a number of interactive resources to explore the spatial distribution of crimes and their dynamics over time, making it possible to identify temporal patterns such as the shift of crime hotspots among nearby locations. Interactive filters allow users to focus their analysis on particular hours of the day, days of the week, and months of the year, making it possible to easily scrutinize the seasonality of crimes. Using different selection mechanisms, users can interactively select regions of interest in various scales, enabling the spatio-temporal analysis of large regions as well as quite specific locations of the city, a trait not

¹community.crimemap.com ²maps.nyc.gov/crime/ ³crimegraphics.com ⁴crimemapping.com

<https://sibgrapi2020.cin.ufpe.br/awards/>



Conclusions

» General - Conclusions

We presented different methodologies that allow a visual Spatio-temporal crime pattern analysis of urban areas considering different characteristics. For that, we have proposed different solutions to tackle the presented problems:

1. we proposed two different methods based on **NMF** and **Stochastic mechanisms** for hotspots identification considering not only the intensity of crimes but also the frequency;
2. we have worked with different levels of spatial discretization such as **census blocks grid-based** and a **high-level discretization** based on street-network to do more accurate analysis;
3. we developed different visual frameworks to represent and visualize **Spatio-temporal crime patterns**.

Each of the proposed approaches has been **designed in close collaboration with domain experts** and deal simultaneously with multiple requirements. These **requirements** are translated into **analytical tasks** that guide the development of victimization systems. Moreover, the set of case studies, experiments, and experts' feedbacks have shown the **usefulness and effectiveness** of the proposed methodologies.

1

Supported by the experiments, the results, and the positive feedbacks, it is safe to say the proposed methodologies have the capability and functionalities to analyze successfully different crime patterns in different scenarios.

2

We introduced **CrimAnalyzer**, a visual analytics tool to support the analysis of crimes in local regions. We also propose a technique based on **NMF** to identify hotspots , considering the intensity and frequency.

3

We introduced **MIRANTE**, a crime mapping visualization system that allows spatio-temporal analysis of crime patterns in a street-level of detail.

4

We introduced **CriPAV** (Crime Pattern Analysis and Visualization), a **street-level** visualization-assisted analytical tool. It is a new methodology to identify crime hotspots based not only on intensity but also on the probability of occurrence, a hotspot grouping technique based on the similarity of crime time series.

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Dr. Claudio silva



Dr. Sergio Adorno



Dr. Marcelo Nery



Dr. Erick Gomez Nieto



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Thank you
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Germain García Zanabria
germaingarcia@usp.br

Visual Analytics for Urban Crime Analysis

