GeoMultiVis: helping decision-making through Interactive Visualizations from Geospatial Multivariate Data

Completed Research

Wagner Signoretti
Pontifícia Universidade Católica
do Rio Grande do Sul, Brasil
wagner.signoretti@acad.pucrs.br

Isabel Manssour
Pontifícia Universidade Católica
do Rio Grande do Sul, Brasil
isabel.manssour@pucrs.br

Milene Silveira
Pontifícia Universidade Católica
do Rio Grande do Sul, Brasil
milene.silveira@pucrs.br

Abstract

The amount of geospatial data that are daily generated through mobile phones, GPS and other technologies, could help in the process of decision-making. We can find datasets with several attributes associated with specific geographic coordinates, such as open government, meteorological and social network data. The visual exploration of such data facilitates to communicate how different attributes correlate to geographical locations by layering these attributes over maps. However, the analysis and knowledge discovery of several attributes associated with a specific location is not a trivial task. In this scenario, we introduce GeoMultiVis, a set of interactive visualizations that combines multivariate data and geospatial localization. It integrates a map with clustered charts and coordinated multiple views, offering a way to interactively apply different filters and analyze several attributes, updating all the related visual representations. We demonstrate its applicability through three real-cases studies. Our main contribution is the interactive visualizations to support the visual analysis of geospatial multivariate data and its application to real cases, helping to find patterns and insights that could support decisions makers to improve social issues in the future.

Keywords

Multivariate Data, Geospatial Data, Visual Analysis, Coordinated Multiple Views, Open Government Data

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Introduction

The popularity of mobile phones, GPS and other technologies used to collect data, as well as the availability of statistical data collected and made available by the government, provides several datasets that could be used to help the decision-making process. Some examples of such data are the ones obtained by sensors, as meteorological data, and open government data, which has several economic and education data associated to each city.

The visualization of such types of datasets enables to communicate how different attributes correlate to geographical locations by layering these attributes over maps. However, there are many difficulties related to the simultaneous display of various attributes, such as the complexity of presenting several values in a simple visual representation and our visual capacity for the rapid recognition of structures with more than two or three dimensions (Chan 2006; Liu et al. 2017). Besides these, there is the need to associate this data with geospatial coordinates. In this context, one of the major challenges is to provide visualization techniques that simultaneously present and relate several attributes associated with geospatial coordinates. These techniques should be easy to manipulate, and its users should be able to identify new information, in such a way that the interaction itself can help to filter the observed data.

Several solutions for the visualization and analysis of multivariate data can be found in the literature (Keim and Kriegel 1996; Wong and Bergeron 1994), though very few were developed for geospatial data (Hempelmann et al. 2018; Oliveira et al. 2016). In addition, to the best of our knowledge, there is a gap in the geospatial multivariate data visualization regarding the possibility to analyze several attributes simultaneously (Fisher, Bynum and Skinner 2009).

In order to bridge this gap, we present GeoMultiVis, a set of interactive visualization for analysis of geospatial multivariate data that facilitates data analysis and knowledge discovery. We are interested in the practice of data science for social good (Zegura, DiSalvo and Meng 2018), considering that GeoMultiVis could be used to help the design and implementation of policies and programs aimed to improve social well-being.

The research methodology we follow for the development of GeoMultiVis[1] consisted of seven steps: (1) literature review to understand the state of the art; (2) identification of the literature gaps; (3) creation of a prototype version with the main functionalities; (4) prototype evaluation through a focus group; (5) application of the suggestions and feedback provided by the focus group; (6) finalization of the prototype development; and, (7) validation of its usage with domain experts. Steps 1 and 2 are covered in the next section, including a discussion about related work on geospatial multivariate data. The proposed interactive and visualization design are described in Section GeoMultiVis, followed by the obtained results with the prototype implementation (steps 3 to 6). The application of GeoMultiVis in three real-case studies, regarding two different contexts (traffic accidents and crimes), is described in Section Case Studies (step 7). Finally, we end this paper with our conclusions and future work directions.

Related Work

In the last few years, several studies have focused on developing novel methods for multivariate data visualization. Whereas most of those papers provide some kind of interaction technique, only a small portion of them was developed for the context of geospatial data.

The analyzed works present interactions from the charts to the map, i.e. the filter operators and selections are applied to the charts and are just reflected in the map (Leite et al. 2017; Oliveira et al. 2016; Spretke et al. 2015; Li et al. 2017). The only interaction that has the map as the starting point is the selection of a

[1] Project available on: https://github.com/DAVINTLAB/GeoMultiVis

specific region (city, country, etc.), resulting in a filter by region to the other charts (Guo 2009; El Meseery and Hoeber 2015; Hempelmann et al. 2018; Zhang et al. 2013). None of them used the map movements to apply filters and restrict the dataset to the region displayed within the map boundaries.

Through the study of the related work, we can see that the most used visualization techniques for geospatial data are Heatmap (Guo 2009; Spretke et al. 2015), Colormap (Zhang et al. 2013; Hempelmann et al. 2018; Leite et al. 2017), and Dotmap (Spretke et al. 2015). These visualization techniques are mainly associated with the following interaction techniques: brushing and linking, with the charts working as filters for themselves and not for the map (El Meseery and Hoeber 2015; Hempelmann et al. 2018); and static filters, available through interface components (Zhang et al. 2013; Li et al. 2017). However, we observed that only a few works allow filtering the map data, usually through components arranged on the side of the map (El Meseery and Hoeber 2015; Hempelmann et al. 2018). Moreover, although there are some proposals for visual analysis of geospatial datasets, the possibility of choosing and changing the charts used to represent each attribute was not found. This is useful considering that the dataset to be analyzed can be associated with different contexts, with their attributes better presented through different charts. Furthermore, it seems that none of them allow analyzing several attributes simultaneously in the map without attributes overlapping.

It was also possible to observe that the existent works do not allow the insertion of generic data, as, e.g., open government data, which are often made available through tables in the CSV format. Their data input is very restricted, requiring specific data formats (Hempelmann et al. 2018; Yang et al. 2017). Also, the data input cannot be changed by the end user, it is done via code changes (Oliveira et al. 2016; Zhang et al. 2013; Li et al. 2017). These findings served as a motivation for the development of GeoMultiVis that is presented below.

GeoMultiVis

To deal with multivariate data, it is necessary to think about a strategy to visually represent and correlate as much information as possible at the same time, as well as to provide different ways for data selection. Then, the challenge is to combine different visualization techniques that give all the information and remains easy to understand, also showing the data of interest once there is interaction with a map or with associated charts. Thus, we propose GeoMultiVis, a set of interactive visualizations that enables the visual analysis of geospatial multivariate data, aiming to support decision-making through visual representations. It provides distinct coordinated visualization techniques to support the analysis of a dataset so that every selection made in one visualization is automatically reflected in the others. It has been designed so that it can be applied in different datasets with a large number of attributes associated with spatial coordinates.

GeoMultiVis allows to simultaneously analyze up to 18 attributes, showing at most 13 of them with clustered markers in the map and 5 of them in associated charts. Fig. 1(A) presents an overview of the map and charts distribution. Its visualization design has the map on the left side of the visualization area, occupying 50% of its total space. In the right side, the other 50% is divided into six blocks: the first one is used for system options and configuration, i.e., to show the total number of records being displayed and to allow changing the cluster icon over the map. The other five blocks are reserved areas for displaying the associated charts with more attributes, e.g., bar, pie, donut, and line charts.

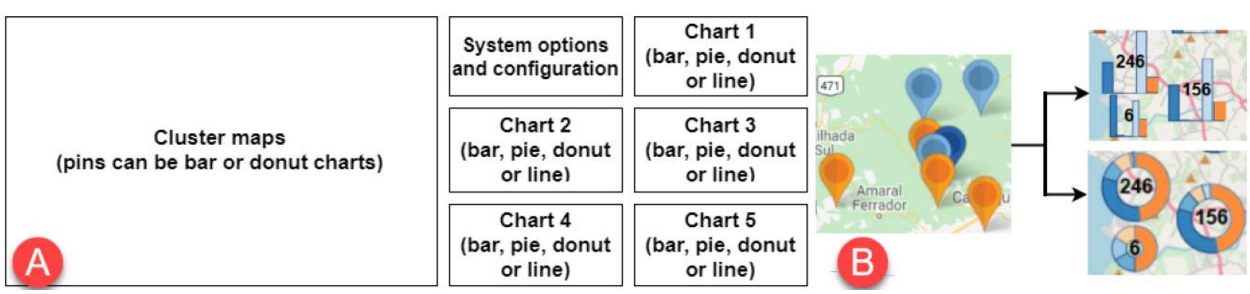

Figure 1: (A) GeoMultiVis map and charts distribution; (B) Clustered markers design.

The use of the map with a large number of markers in a small area may cause some visualization problems (Meier and Heidmann 2014). In low zoom levels, the number of markers displayed per square inch increases dramatically (in fact, quadratically with respect to the zoom factor (Frank and Timpf 1994)). Then, the positions of markers on the maps converge more and more until they are overlapping each other partially or entirely. The problem gets even worse when there is too much data to plot in the same regions. On the other hand, after zoom in, objects are larger but fewer are in the field of view, leading to a loss of context. The solution is to use a cluster map, since the clustered area may provide insight for increasing computational efficiency when faced with larger quantities of points than we typically need to address. Instead of using only one simple marker to represent the clustered data, and since we want to present multivariate data, we decided to group the data into bar and donut charts. Thus, it is possible to represent several attributes in only one point, and when a zoom out is applied, multiple markers are clustered in a nearby location.

Fig. 1(B) describes how clustered markers that are exhibited in the map were designed. When multiple markers are displayed at the same time, it causes overlapping issues. These markers, even overlapped, are differentiated by different colors indicating different properties. The bar and donut charts work similarly, considering the number of markers of each category to define the chart properties. Each cluster is created considering a radius of 80 pixels, thus all markers included in this area are aggregated. Zoom changes on the map will cause changes on the clusters, which will be redesigned considering the new area.

The five associated charts proposed to be used in GeoMultiVis could be of different types, like pie, bar, donut, bubble or line chart, or even parallel coordinates. The choice should be made according to the characteristics of the attribute that will be presented. For example, a pie chart is a good option for showing the relative sizes of parts of a whole, while a bar chart could provide an accurate estimate for comparing values, and the line chart is best suited for representing data associated with a timeline.

GeoMultiVis interaction starts with the dataset definition and attributes selection. It accepts multivariate datasets with geospatial information organized in a tabular way. It means that it is mandatory to have a spatial coordinate (latitude and longitude) associated with each record. The other columns should contain quantitative and qualitative attributes that can be presented in the map or in the associated charts. Since it can display several attributes at the same time, and each attribute must be presented in each column, datasets with a large number of attributes to be explored can also be used. Then, it is necessary to select the attributes to be explored and associate each one with the desired visual representation. According to this selection, some attributes are clustered on the map and others are presented in associated charts. However, both the dataset and the selection of attributes can be changed at any time, just redefining the dataset or the mapping, and generating the visualizations again.

GeoMultiVis uses brushing and linking integrated with CMV (Roberts 1998; Roberts and Wright 2006), and panning. Brushing and linking is an interactive visualization technique that connects two or more views of the same dataset, then any modification in the representation in one view will influence the representation in the other views (Baeza-Yates and Ribeiro-Neto 1999). This technique has been integrated with CMV in several applications and visualization tools for interactive exploration (Bostock et al. 2011, Ogievetsky and Heer 2011). The interaction techniques panning and zooming are used to allow the user to change the scale of the map, navigate through information spaces and apply filters to the visualization (Cockburn and Savage 2004).

Another design decision we made is that any chart presented in Fig. 1(A) can be used as a selection filter. Moreover, the most promising interaction technique of GeoMultiVis is the possibility of using the map as a filter. This means that as zoom and pan interactions occur, the data displayed in the associated charts are limited only to the perimeter that is being displayed on the map. In other words, every time the map area that is being visualized changes, all the associated charts are updated to show just the data associated with the selected new perimeter.

Prototype implementation

The following subsections present the first proposal of GeoMultiVis, its initial analysis, and its implementation refinement.

First Proposal

In order to validate GeoMultiVis idea, we made its first implementation using Google Maps API[2] and D3 (Bostock et al. 2011). The organization of visual components, i.e. map and associated charts, was the same presented in Fig. 1(A). Initially, just one categorical attribute could be represented on the map, with the cluster markers displayed as bar charts. The associated charts were implemented with bar, pie and line charts. Although it was possible to filter values through the associated charts, interactions on the map did not reflect the charts in this version. To test this implementation, we use open government data containing records of traffic accidents (see Section Traffic Accidents for details). The markers on the map displayed as bar charts exhibited the total number of accidents types, each one with a different color. Our main goal with this implementation was to have a functional proof of concept to be analyzed.

Proposal Analysis

To analyze which visualization techniques would assist the understanding of the presented data, as well as to analyze if GeoMultiVis allow gleaning insights from a dataset, a focus group was carried out (Morgan 1997). The purpose of the focus group was to present the initial version of GeoMultiVis to a heterogeneous group and collect their suggestions and feedbacks in order to refine and improve it. The group was composed of seven participants, with ages ranging from 22 to 43 years old. Five of them were from computer science area with expertise in data visualization, one participant was graduated in geography and works with geospatial analysis and data science, and one participant was from statistics and economics with experience in statistics and open government data. Two moderators, who were researchers in the data visualization area, conducted the activities.

Initially, we performed three activities to introduce the subject: choose a visualization technique for geospatial data that would best represent a given question; perform a quick analysis of some visualization tools[3] to identify the most relevant features to present multivariate data on the map; illustrate how they would represent a given scenario by drawing it on a printed map. After that, the first implementation of GeoMultiVis was presented through a real-time demonstration, in which participants could suggest improvements and discuss its functionalities, interactions, and visualization techniques.

All participants said they were able to easily identify the GeoMultiVis features, and everyone agreed that it could be applied to different contexts and different datasets. Among the possible applications they mentioned: (1) crime occurrences per city, connecting this dataset to socio-economic information and providing comparisons of different areas; (2) education level to compare if the distribution of federal funds impacts on that; and (3) comparison of the relationship between maintenance and flooding in the big cities. A participant said that "Almost any dataset containing quantitative and qualitative data could be applied to GeoMultiVis". Besides that, all participants believed it assists in data analysis. The interaction design was highlighted as the strongest point, as well as its implementation and clarity of information.

Some suggestions of improvement included: the automatic adjustment of the charts scale; the inclusion of the charts' title; the possibility of applying filters to the charts by moving the map; the use of heatmaps to represent multiple categorical attributes; and, the replacement of the bar chart by a donut chart as marker cluster on the map, using transparency, so that the user could see the map and the chart simultaneously.

Implementation Refinement

After collecting the feedback and suggestions, we improved GeoMultiVis. Fig. 2 presents its last implementation composed by the map and associated charts, using the data described in the Section Traffic Accidents as input data. In order to implement the interactive visualization, we are now using different technologies. Instead of Google Maps API we are using Leaflet, motivated by its flexibility in creating icons for marker clusters. To draw the marker clusters as donut and bar charts we are using D3. Crossfilter[4] is being used to create the interaction with coordinated views, connecting the charts among themselves and to the map movements, and Turf.js[5] to reduce the dataset to the perimeter being displayed on the map.

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[2] https://developers.google.com/maps/

[3] https://www.qlik.com/us,https://www.oracle.com /solutions/business-analytics/business-intelligence/index.html,https://powerbi.microsoft.com

[4] http://square.github.io/crossfilter/

[5] http://turfjs.org/

For the attribute "accident type", we choose to exhibit the clustered markers on the map as bar charts (Fig. 2(3)). When we move the mouse over the markers, the region that corresponds to the clustered data is highlighted (Fig. 2(2)). The identification of each bar is also presented in the left (Fig. 2(1)). Operations such as zoom and pan are available through mouse interactions, and the first one is also available through the buttons plus and minus (Fig. 2(1)).

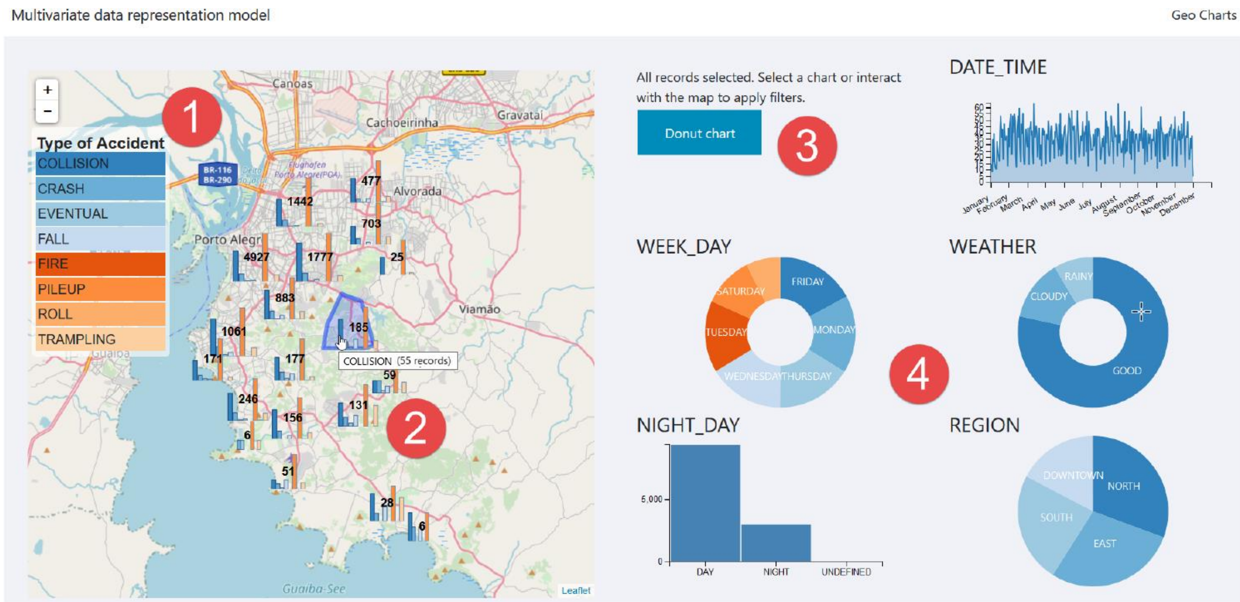

Figure 2: Final implementation of GeoMultiVis.

Considering the first implementation, the major changes in the associated charts (Fig. 2(4)) to meet the improvements suggested in the focus group are: (a) all charts have a title describing what attributes they are displaying; (b) the color palette was updated to use neutral colors to avoid misleading associations of attributes or values that are not necessarily related; (c) donut charts as an option for the marker cluster; and (d) charts' choice according to the attribute being visualized. Moreover, the interaction techniques are fully implemented, including the use of map movements as a filter, then only records respecting that specific perimeter are displayed in the associated charts; CMV with the charts working as filters to the map and vice-versa; and, highlighted clustered boundaries with a blue polygon on mouse over.

Fig. 3 shows two possibilities of clustered markers that can be used on the map, exemplified with the data described in the Section Traffic Accidents. The first one (Fig. 3(1)) correspond to donut charts presenting the type of accident in different colors and displaying the number of records clustered in the center. It also exemplifies the mouse over functionality, which is responsible for highlight the cluster boundaries. The second type of clustered markers (Fig. 3(2)) corresponds to bar charts with the number of records overwritten on it. This example presents the use of five different attributes at the same time, and each bar represents the sum of the value of each attribute: number of accidents with cars, number of deaths, number of posterior deaths, number of injuries and number of accidents with motorcycles. Both clustered markers support the visualization of a single attribute with categorical or quantitative data and also supports the visualization of multiple attributes with quantitative data by adding up the values in the clustered perimeter to represent it with the proportional bar size.

Considering that the visualization and interaction techniques can be applied to different datasets presented in a tabular format, it is important to provide the option to choose the chart that best represents each attribute. Therefore, we provide a simple graphical interface to enable the selection of the attribute(s) that will be clustered on the map (Fig. 3), the ones that will be represented in each chart (Fig. 2(4)), and the type of chart for each selected attribute. It is possible to upload any dataset in the CSV (comma-separated values) format and define where and how these attributes should be displayed. The attributes latitude and longitude are automatically recognized as geographical location information. Then, just the other selected attributes will be considered to generate visualizations. As an example, there are 5 different attributes in Fig. 3(2) each one containing quantitative information. Each accident might involve multiple cars, deaths, subsequent deaths and motorcycles. The total number of each attribute is considered to design the respective bars on the charts.

Case Studies

In order to demonstrate the applicability of GeoMultiVis, the following subsections show its use in three case studies, about two different contexts: traffic accidents and crime. We choose these open government datasets because they are multivariate, with many attributes.

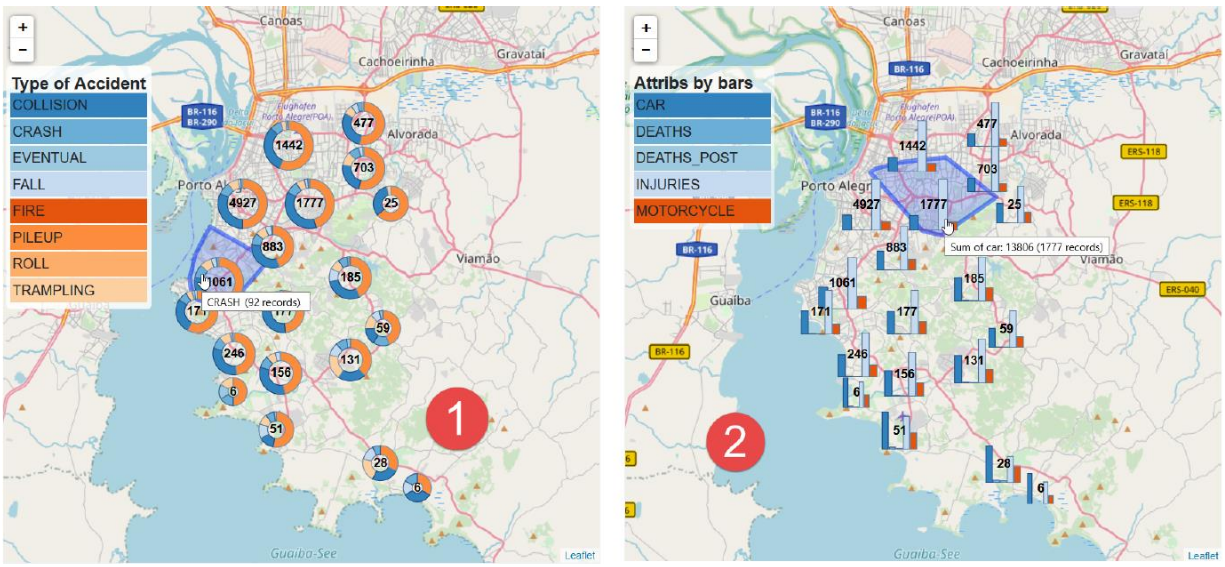

Figure 3: Examples of clustered markers that can be used.

Traffic Accidents

The first context deals with traffic accidents. We used datasets from 2000 to 2016 of Porto Alegre[6] (a city in the South of Brazil). These records generate large multivariate datasets, with several attributes associated with a specific location (latitude and longitude). Fig. 2 presents the dataset in use. In this visualization, the attributes date, the day of the week, weather, day period and region are represented in the associated charts (Fig. 2(4)). The remaining attributes (type of accident, latitude, and longitude) were used to create the marker clusters over the map.

When visualizing the dataset in GeoMultiVis, it is possible to understand the existent relationship between the variables, allowing a visual analysis in which we can easily see, e.g., the days with more accidents, the most common types of accidents and the roads with more accidents. Crossing the data, we can make some relations such as the increase of accidents on the weekends and car pileups as the most common type of accident. It is not possible to know the number of pileup accidents that occurred during the weekend or under rainy days, e.g., by simply looking to the charts. The filter combination on the charts and interaction on the map can provide an accurate conclusion for that.

Fig.3 shows two different visualizations for this dataset in the map. Analyzing the maps and associated charts, we observe that the number of injuries is usually higher than the number of cars involved in the accidents, and usually there are no deaths resultant of these accidents. We also notice that even with the cycle routes built in recent years in the city, the number of accidents involving bicycles remains stable over the last five years. The analysis of such data may have a positive impact since it allows the implementation of policies and programs, e.g., to reduce car accidents, improving social well-being.

[6] http://datapoa.com.br/dataset/acidentes-de-transito

Crime

The second context is about crime. The first study uses data about the crimes registered in the municipalities of Rio Grande do Sul (a state in the south of Brazil). These data[7] have several quantitative attributes associated with each municipality. Fig. 4(1) presents 13 different attributes using bar charts as a marker cluster. These attributes are related to crime categories, such as weapons-related offenses and ammunition, corruption-related offenses, larceny, and extortion, among others. The map visualization makes possible to identify areas with more crimes and the most common crime categories per municipality. In this case, we can see that the most common category of crime in all municipalities is theft. Moreover, when clicking on the final marker all attributes that were used to compose the chart are displayed, as exemplified in Fig. 4(1).

A similar crime dataset was used to create the third case study, with crimes from Bethesda, MD, USA[8], as shown in Fig. 4(2). The main difference is that instead of grouping the clusters by municipality this one group the clusters by its specific geographic location. In addition, there were fewer crime categories to be mapped. By analyzing these data, it is possible to identify the most common crimes in each region, for then getting people to engage with preventive actions.

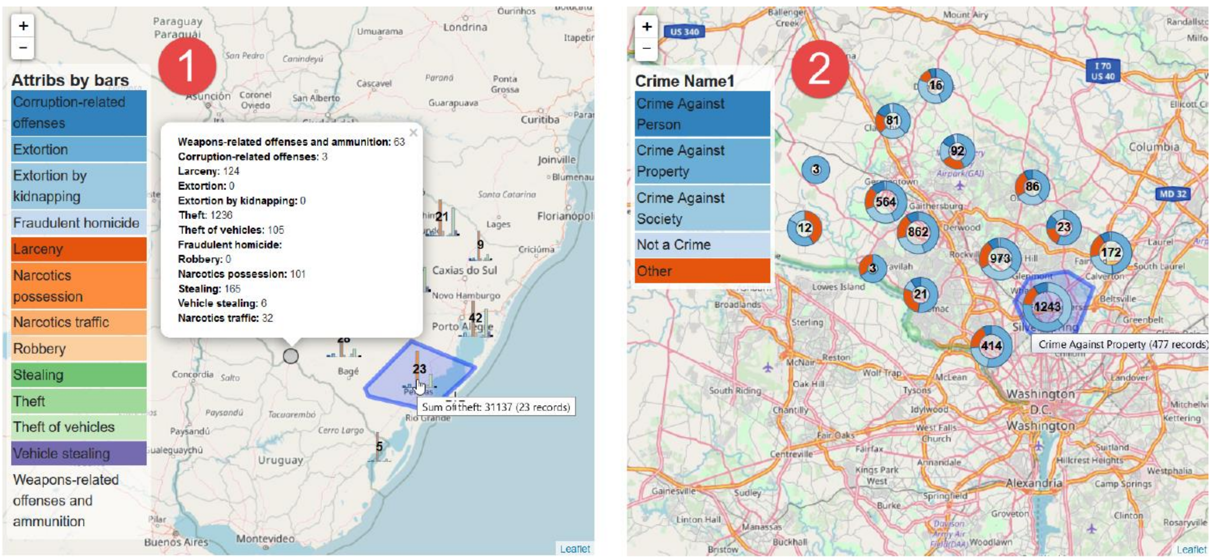

Figure 4: Case studies with crime data from Brazil (1) and USA (2).

Expert Analysis

In order to analyze the effectiveness of GeoMultiVis, we conducted in-depth interviews with three domain experts. They were selected because of their background in data visualization and open government data. We used semi-structured interviews with a set of guiding questions allowing for enough space for open detailed statements of the interviewee (Aghamanoukjan, Buber and Meyer 2009).

The first interviewee (I1) is an IT architecture manager that works with analytic software such as Tableau; the second interviewee (I2) is a Computer Science University professor and researcher with experience analyzing open government data; and, the third interviewee (I3) is a master degree student whose research is in the area of visualization of geospatial data. Interviews lasted about 30-40 minutes per interviewee and their audios were recorded. Before starting it, the interviewees could manipulate GeoMultiVis and discover its features. After that, they were prompted to perform the following tasks:

- Use the traffic accidents dataset (Fig. 2) to find the region with more accidents on Saturday's rainy days, the most common type of accident in this case, and what is the region with more accidents at night.

[7] http://visualiza.fee.tche.br/crime/
[8] https://catalog.data.gov/dataset/crime

- Use the crime data grouped by municipalities of a state (Fig. 4(1)) to find the type of crime with more records in general and in the metropolitan region of the state capital.

The three interviewees were able to easily perform the tasks and find the answers. I1 observed "*the use of the map as a filter is a differential of GeoMultiVis, the way the zoom works adapting the clusters' size and the way the clusters are resized according to the zoom interaction are good*". I2 mentioned that "*the visualization and interactions help in data analysis*". I3 observed "*the visualization of several attributes at the same time as one of the strengths of GeoMultiVis. The filters applied through the interaction help him to understand the attributes' relationship*". I3 also mentioned "*the GeoMultiVis flexibility as a positive factor since any dataset with geospatial location can be visualized through its interface*". Its applicability to different contexts was highlighted by all the three. Some suggestions are to use only donut charts instead of the pie charts, the inclusion of parallel coordinate and radar charts, and some particularities about specific buttons and icons.

The interviewees' discussions regarding traffic accidents and crime occurrences demonstrate that they understood the effect of their actions. Their verbal comments during and after interacting with GeoMultiVis show us that the implemented visualization and interaction techniques are useful and helpful in the comparison of multiple attributes simultaneously. According to the participants, GeoMultiVis provides a detailed overview of the dataset and also detailed information of all attributes by using the filters present on all visual components.

Conclusions and Future Work

The growing availability of geospatial multivariate data could help in the process of decision-making in several areas. However, the difficulties related to the analysis of different attributes bring the necessity to provide alternatives to help who is interested in knowledge discovery. The visualization of such types of datasets allows a better understanding of the attributes and geographical locations correlations. But the way we correlate this multivariate data in one (or more) visualizations is still a challenging issue.

Considering this scenario, we presented GeoMultiVis, a set of interactive visualizations, designed to be used by novice users, without technical skills, and also for any type of geospatial multivariate data in a tabular format. Our main contributions include: (1) a visual strategy that allows to represent several attributes on the map with dynamically linked charts associated; (2) an interactive approach based on the brushing and linking technique integrated with coordinated multiple views to support visual analysis; and, (3) the use of the proposed set to analyze open government datasets. These contributions are directly associated with knowledge discovery and decision-making and could help the design and implementation of policies and programs aimed to improve social well-being. Besides that, GeoMultiVis' ease of use allows any citizen to analyze the available open government data, improving his/her participation in this process.

Currently, we are using GeoMultiVis in a comparative study with other visualization tools, focusing in analyze how visualizations could support the identification of the effects of two specific traffic policies. As next steps, we intend to deepen our investigation analyzing the impacts of GeoMultiVis in the decision-making process through its use in a periodical way for daily analytics tasks, and evaluating different metrics like performance, scalability and accessibility, for instance.

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