

Evaluating Interactive Comparison Techniques in a Multiclass Density Map for Visual Crime Analytics

L. Svcarovic¹, D. Parra^{1,3}  and M. J. Lobo²

¹Pontificia Universidad Católica (PUC), Santiago, Chile

²LASTIG, Univ Gustave Eiffel, ENSG, IGN, F-94160 Saint-Mande, France

³Millennium Institute Foundational Research on Data, Santiago, Chile

Abstract

Techniques for presenting objects spatially via density maps have been thoroughly studied, but there is lack of research on how to display this information in the presence of several classes, i.e., multiclass density maps. Moreover, there is even less research on how to design an interactive visualization for comparison tasks on multiclass density maps. One application domain which requires this type of visualization for comparison tasks is crime analytics, and the lack of research in this area results in ineffective visual designs. To fill this gap, we study four types of techniques to compare multiclass density maps, using car theft data. The interactive techniques studied are swipe, translucent overlay, magic lens, and juxtaposition. The results of a user study ($N=32$) indicate that juxtaposition yields the worst performance to compare distributions, whereas swipe and magic lens perform the best in terms of time needed to complete the experiment. Our research provides empirical evidence on how to design interactive idioms for multiclass density spatial data, and it opens a line of research for other domains and visual tasks.

CCS Concepts

• **Human-centered computing** → *Empirical studies in visualization; Visual analytics;*

1. Introduction

Multiclass maps are data visualizations where each data point has multiple attributes, at least two spatial attributes (typically latitude and longitude) and one categorical, which values represent different classes. Multiclass density maps are defined as multiple density plots with different classes [JVDF19]. These kinds of visualizations are required for diverse application areas in geographical data analysis, such as election data visualization or crime analysis. For example, when exploring crime data related to stolen vehicles, experts are interested on visualizing the geographical area of a theft, and additional attributes, such as car brand and type. Furthermore, they are also interested in temporal trends by comparing the data at two different moments in time. However, there is still a lack of guidelines to inform the design of visualizations to support visual comparison tasks involving multiclass density maps.

Recently, Jo et al. [JVDF19] proposed a declarative rendering model that defines a design space for multiclass density maps, which can be adapted to this problem. Nevertheless, if the analyst has to conduct comparisons, she will need to relate two multiclass density maps, and perform a visual comparison task. The problem of visual comparison has been studied both using static visualizations [OJEF19] and interactive techniques [LPA15], where results suggest that overlaying visualizations is more effective than juxtaposing them.

However, those studies either address geographical maps [LPA15] or abstract information visualizations [OJEF19]. To the best of our knowledge, no study has yet compared interactive techniques for visual comparison of multiclass density maps. Inspired by the study by Lobo et al. [LPA15], we conducted an evaluation to contrast four comparison interaction techniques – juxtaposition (JX), transparent overlay (OV), magic lens (ML) and swipe (SW)– in the domain of crime analytics. We developed two hypotheses and we tested them empirically ($N=32$), to understand the effect of these techniques. The results suggest that when comparing distributions with small differences (high difficulty), JX is the less effective technique, producing significantly fewer correct answers. Subjects using JX also require more time than other techniques to complete the tasks under various conditions. On the other hand, SW has a consistently good performance specially in terms time to complete the tasks. We discuss how these results relate to the previous ones [LPA15], and we conclude with some preliminary design guidelines and ideas for future research.

2. Related Work

Comparing visualizations. Gleicher et al. [GAW*11], review multiple examples of visual comparison in visualization and categorize them as *juxtaposition*, *superposition* and *explicit encoding*.

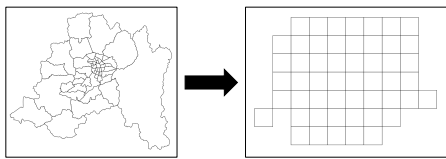


Figure 1: Map of the communes (sub regions) in the Metropolitan area of the city of Santiago. On the right side, the grid version of the sub regions (cells), created with *Small Gaps* [MDS*16].

Later, Javed and Elmquist [JE12] further specify the classification with four means to achieve visual composition: juxtaposition, superimposition, overloading and nesting. However, there is still little evidence about which of these methods is more efficient, although some recent studies attempt compare different techniques. Peña-Araya et al. [PAPB19] compare different visualizations to identify trends across time and space, small multiples being one of the studied techniques. However, these studies compare non interactive techniques. In this paper, we are interested not only in comparing the visual arrangements but also the interaction techniques that enable the user to manipulate these arrangements. Multi-scale interaction techniques present two visualizations at the same time, to enable the inspection of regions of interest while keeping the context visible [ACP10, BAP10, JE12, BSP*93]. However, these techniques focus on comparing the same region at different scales, whereas our study focuses on techniques to compare spatially aligned visualizations. Some techniques are especially designed for combining geographical representation [LB19] or to support other tasks related to visualizations [PF06, YKSJ07, PBH*15], but they are not designed for multiclass density map comparisons.

Multiclass visualization. Multiclass maps are in general represented by using multiple visual channels or aggregating and filtering data [AA99, CLW13, KHD*10, MAF15, Gle18]. Jo et al. [JVDF19] introduced a design space to represent multiclass density maps based on a *class buffer model*, to make visualization more expressive and scalable by using various visual channels. Instead of using visual channels, Chen et al. [CCM*14] propose to change point spatial distribution according to their relative density. **Visual crime analytics.** However, these visualizations are static designs and do not consider how to interact with them. Furthermore, to the best of our knowledge, there is not yet an empirical study that compares them. Some visualizations address specifically crime data, in order to gain insights about criminal behavior. For example, Nakaya et al. [NY10] use a 3D visualization to visualize geographical coordinates and time. Levine et al. [Lev06] combine a map with statistical data in order to infer spatial relationships. Brundson et al. [BCH07] compare three different spatio temporal visualization techniques to detect crime patterns; animations, small multiples, and isosurface. In this article, we focus particularly on visual analytics of car theft data. Interpol has reported evidence of the links between car theft and other crimes of higher social impact such as human and weapon trafficking [GB08], making it an important case of study.

3. VISUALIZATION AND INTERACTION DESIGN

The main goal of our idiom is to enable comparison of multiclass data among different regions in a map, but also upon different moments of time on the same region.

Visualization idiom design. Our design assumes that there is a pre-defined spatial area divided in sub regions. Using this input, we can choose among the design alternatives by Jo et al. [JVDF19] to visualize a multiclass distribution inside each region. However, in a map where sub regions' size vary significantly (such as London's boroughs), encoding multiclass distributions with bar plots might be ineffective for visual comparison, as well as using kelp diagrams [DVKSW12] or bubble sets [CPC09]. We then turn the original spatial map into a grid layout where every cell, representing a sub region, has the same size. We use *Small Gaps*, introduced by Meulemans et al. [MDS*16], to divide a metropolitan city map into equally-sized smaller sub regions (cells) and maintaining their relative positions, as shown in Figure 1.

Plotting a distribution inside each cell. The most effective idiom to represent a categorical distribution is the bar plot, because of the length channel [Mun15]. However, this makes sense only if we compare categories within the same bar plot, but if we compare categories among different bar plots in different spatial regions, their axes are not aligned, and then the length channel's effectiveness for the bar mark drops [Mun15]. In addition, with this idiom there might be large amount of empty space which could be used to encode other information. Designs such as Google's Facets Dive [WPB*19] show that filling an area could be a good idea to compare multiclass distributions in grid layout. Other authors have also visualized distributions by filling the whole area of cells in a grid, such as the weaving patterns of the high-frequency textures by Hagh-Shenas et al. [HSKIH07]. We then combine the ideas of Google facets and Hagh-Shenas et al. to design an idiom which maximizes the use of space but at the same time does not decrease the information-carrying capacity of color weaving with more than 6 classes, as shown in each squared sub region in Figure 2.

Interaction idiom design. The tasks for comparing multiclass distributions guided our interaction idiom design. The closest research to our study is the work by Lobo et al. [LPA15], who contrasted five techniques for map comparison, but they did not compare multivariate distributions in spatial regions. In their study, they asked users to find differences between a satellite image and a topographic map of the same region, with artificially introduced differences. In this study, we use four of the five techniques they considered: Swipe (SW, Figure 2(a)), Translucent Overlay (OV, Figure 2(b)), Magic Lens (ML, Figure 2(c), our equivalent to their Blending Lens), and Juxtapose (JX, Figure 2(d)). Lobo et al. [LPA15] concluded that translucent overlay (OV) and Blending Lens (our ML) reported the best performance, while Swipe (SW) performed poorly, and Juxtapose (JX) just slightly better. Our intuition is that the differences among their task [LPA15] (identifying objects added, edited or removed in maps) and ours (comparing distributions in maps) can result in different conclusions.

The rationale for choosing these techniques is given by how differently they cover three aspects: (i) visual interference, (ii) divided attention, and (iii) exploration type. This analysis is similar to the one made by Lobo et al. [LPA15], but we introduce a new context, since subjects have to compare sub regions, distant from each other, on the same map. We now introduce the concept of *layer*. Figure 2 shows the distribution of car brands stolen in each commune in the year 2016, that is an information *layer*. If I want to compare to the

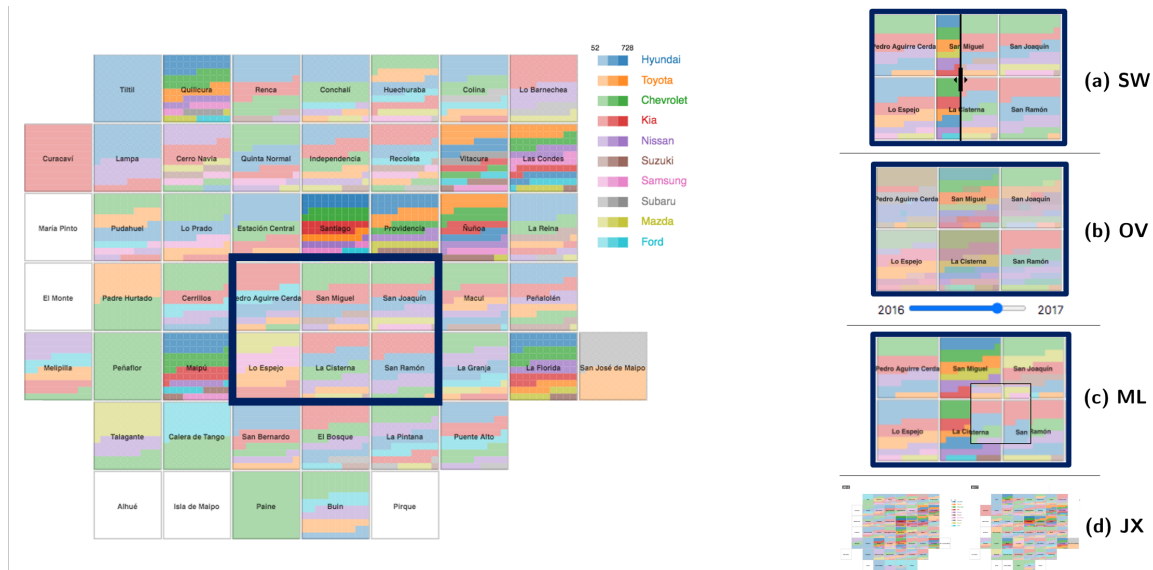


Figure 2: The main view, where squared cells are the communes within Santiago city, and colors indicate car brands. The right side shows zoomed views of the four comparison techniques: Swipe (SW), Overlay (OV), Magic Lens (ML) and Juxtapose (JX), which shows two maps.

distribution of thefts in 2017, I am comparing two layers, 2016 vs. 2017. Next, we describe the four comparison techniques evaluated.

Swipe (SW). Figure 2(a) shows this technique. In SW, users move a slider with arrows in order to unveil the distributions presented on one layer (e.g. 2016) compared to those on a different layer (e.g. 2017). When a user compares information from different layers over the same sub region, SW does not divide users' attention and there is no visual interference, but it requires motor exploration.

Translucent Overlay (OV). This technique allows users to compare layers of information by letting them choose the opacity of one layer with respect to another using a slider outside of the map, as shown in Figure 2(b). OV does not divide users' attention but introduces visual interference.

Magic Lens (ML). The magic lens, in Figure 2(c), allows the user to move a square acting as a lens, unveiling multiclass information of a different layer. This interaction allows a personalized exploration within a specific visited area. The magic lens does not directly divide the attention on different areas, but requires significant motor interaction as well as an increased visual interference compared to SW or JX.

Juxtapose (JX). Juxtapose (Figure 2(d)) presents the information in two coordinated ML views displayed side-to-side, implying a small visual interference but a high level of divided attention (compared to OV, ML and SW).

4. User Study: Car crime analytics

Context. For this study, we focus on crimes taking place in the Metropolitan Region, where Chile's Capital, Santiago, is located. Nowadays, analysts interested on this information use tools such as Excel to inspect the data, as well as using some standard plots such as pie and bar charts. They are also interested on understanding existing spatial patterns and how they evolve over time. Because analysts working on insurance data are interested on preventing car thefts, they consider car classes such as the kind of car (automobile, station wagon, truck, etc.) and the car brand (Toyota, Hyundai,

etc.). These data varies from year to year, then analysts have to compare data from pairs of years chosen on demand.

Tasks. In order to investigate the different interaction techniques for multiclass density map comparison, we use the task mentioned before, comparing two multiclass maps from two different years. We propose two kinds of tasks: *one county* (i.e., one commune) comparison across two years and *two counties* comparison across two years, both distributed across three levels of difficulty: *easy*, *medium* and *hard*. The *One county* task requires the participants to compare the same county across two years and identify if the proportion of a specific class value (e.g., proportion of Hyundai stolen) is *higher*, *lower* or *the same*. A *two counties* comparison task requires participants to identify the relationship between two counties in two different years, for example, in which year the county A had a bigger proportion of thefts belonging to class c (e.g. station wagon) than county B. Each question has three possible answers: *year 1*, *year 2*, and *same*. Finally, we consider three levels of task difficulty (easy, medium, hard). For *one county* tasks, the smaller the difference between two distributions, the more difficult the task. For *two counties* tasks, the difficulty additionally depends on the Manhattan distance between the counties to compare, since it enhances the divided attention as in JX, Figure 2(d).

Hypotheses. Based on Lobo et al. [LPA15] as well as our analysis in section 3 we hypothesize that:

H1: Techniques that superimpose the visualization (ML, OV, SW) will be more efficient than techniques that juxtapose them, because divided attention has higher impact than visual interference.

H2: Visual-driven scanning will be more efficient than motor-driven, thus OV will be the most efficient technique.

Participants and Apparatus. Thirty-two unpaid volunteers (20 males, 12 females), age 16 to 32 years old, participated in the experiment. The experiment was run on a MacBook Pro 15" from 2017, equipped with a graphic card Radeon Pro 2 GB and an Intel

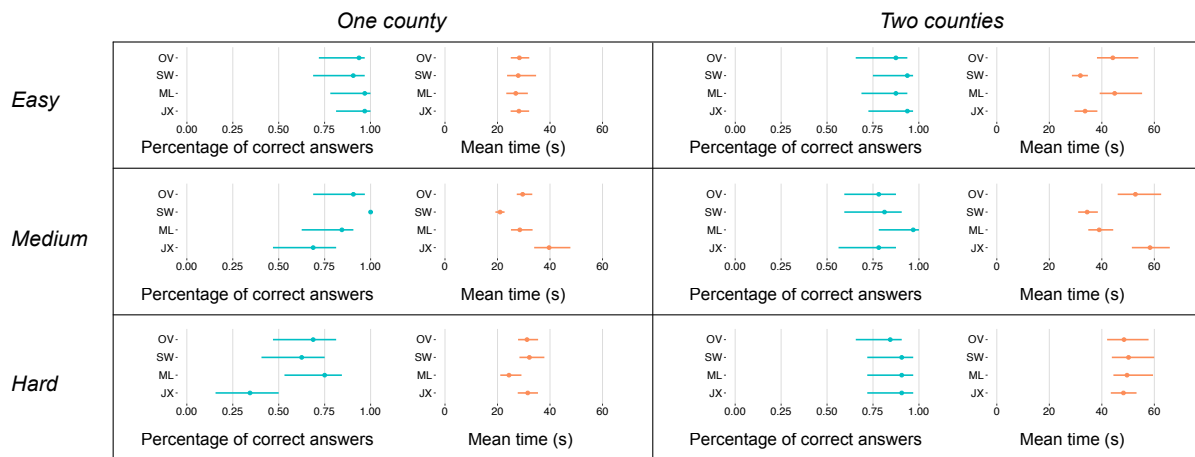


Figure 3: Percentage of correct trials and mean time per each question type and difficulty. In the task comparing one county over two years, under the hard difficulty condition, JX was significantly less effective to identify differences in distributions. In terms of time, SW requires significantly less time than the others to finish the visual comparison task in three out of six conditions.

Core i7 2.8 GHz processor, and 16 GB RAM. We used an external display of 27", and a standard optical mouse.

Procedure. We followed a [4x2x3] within-subject design with 3 factors: TECHNIQUE, TYPE of question and DIFFICULTY. TECHNIQUE refers to the interaction technique used, ML, OV, JX and SW, TYPE of question is either ONE COUNTY or TWO COUNTIES and the level of difficulty EASY, MEDIUM or DIFFICULT as detailed before. Trials were grouped by TECHNIQUE and the TECHNIQUE order was counterbalanced across participants using a latin square. Each block presented one question of each TYPExDIFFICULTY combination ordered by difficulty level, and a training trial at the beginning. Before starting the experiment, participants answered a series of questions related to their previous knowledge about information visualization and the location of counties in Santiago. After answering the 24 questions, participants ranked the difficulty of the techniques, and the difficulty of both question TYPES. All questions and all the study data can be found in the supplemental material.

5. Results and Discussion

We base our analysis on 95% bootstrap confidence intervals (CIs) [Dra16]. CIs have been used in visualization studies, [PAPB19, BBB*19], and are recommended over p-values to avoid dichotomous thinking [BD17]. We share a web site with materials of the statistical analysis [†].

Discussion. Our results indicate that under small and medium difficulty tasks, all techniques reach in average at least 75% of success rate, with no difference between them for accuracy, excepting for SW in the ONE COUNTY task under medium difficulty: 100% of correct answers. However, under tasks of larger difficulty, JX drops in performance with a % of correct answers between 25% and 50% (Figure 3). In terms of time consumption, the differences are not very large, but we can still observe a clear pattern summarized in Figure 3. There is a trend showing that the time needed to complete the tasks using swipe (SW) is smaller than OV and JX in three out of six conditions, and ML reports the best results in one condition,

while not being significantly different from SW in four out of six conditions.

The results support **H1**, since JX resulted in a decreased rate of correct answers as well as longer time to complete the tasks. Interestingly, JX reported worst results even in the task that required the users to compare distributions from two counties. The results indicate that this setting amplified the attention problem, probably because the system was designed to highlight the same sub region in both juxtaposed views. One potential solution, which requires an additional study, is to highlight one sub region on the left-side map, while highlighting another one (to be compared) on the right-side map. However, **H2** is not supported. Contrary to previous studies [LPA15], SW is as effective and faster than OV. Because the multiclass maps being compared are more visually similar than the maps compared by Lobo et al. [LPA15], the visual interference might be more relevant here, making ML and SW more effective.

6. Conclusion

In this article, we studied four techniques for visual comparison on multiclass density maps. We conducted an empirical evaluation using car crime data. Although more research is necessary, the results indicate that juxtaposition (JX) is the less indicated technique for comparison tasks in multiclass density maps, while magic lens (ML) and swipe (SW) are the ones consuming less time under different conditions. The main limitation of our work is that we tested only one type of visualization idiom, so in future work we will test these techniques using different visualization idioms (bar plots or pie charts). We would also like to provide guidelines to improve these techniques in order to make them more effective and less time consuming. We will also identify other application domains to generalize our results.

7. Acknowledgements

This work was funded by ANID - Millennium Science Initiative Program - Code ICN17_002 and by ANID, FONDECYT grant 1191791. We also thank Richard Weber and the FONDEF IDEA grant ID16I10222, as well as Cristobal Eyzaguirre for his initial JS implementation of the high-frequency texture pattern.

[†] https://mjlobo.github.io/multiclass_ev2021/

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