Empirical Evaluation of Open Government Data Visualisations

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***Abstract*—The Open Government Data (OGD) movement has seen governments around the world embrace the concept of opening their data. However, the large amounts of data released have not resulted in wide acceptance of the data by end-users. This is partly due to the emphasis on *machine-readability* rather than *human-usability*. Recently, some data portals have included visualization techniques to make the portals more usable. In this work, we report on user studies conducted to evaluate different OGD visualization techniques. The techniques were evaluated both quantitatively, through recorded tasks, and qualitatively, through a post study survey. We found that geographic map visualizations were reported by users to provide the highest level of qualitative satisfaction, which correlates with the quantitative results requiring the shortest time to complete the tasks. This study provides insights into empirical evaluation of visualization techniques to aid OGD providers in making decisions about the best way to present data in their portals.**

Keywords- ***data visualizations*; *open government data*; *empirical evaluation*;**

I. INTRODUCTION

The amount of OGD released for public use, reuse, and redistribution is rapidly growing. Currently, 18 million OGD datasets have been published around the world [1] and according to dataportal.org there are 520 registered government portals [2]. At the International Open Government Dataset Search there are 192 catalogs in 24 languages representing 43 countries [3]. These numbers represent a growing supply of OGD for users. However, the uptake by users has been limited. One possible cause, which we investigate in this paper, is the limited usability of open data.

The primary focus of the OGD movement has been on ensuring the release of the data so that it can be accessed. Additionally, the desired format of the data is one that is machine-readable, in formats such as Comma Separated Values (CSV) and eXtensible Markup Language (XML), preferably in the most raw and primal forms [20]. The motivation is based on transparency, so that the community has access to the data in its original form without modification. A downside to this motivation is that it is only usable by a small percentage of the community, those with technical computer skills, such as computer programmers and data analysts. The focus on *machine-readability* has limited the data's *human-usablility* [17].

One strategy to increase end-user uptake of OGD is to present the data using visualizations [18][19]. Graves and Hendler [4] conducted a detailed study on the use of visualisations for OGD. Their research focussed on end-users with some knowledge of data analysis such as researchers, journalists, and government data providers and consumers. They also identified a user profile of “Common Citizen” but did not include them in their study. They expressed an interest to investigate the remaining open question of how to empower “Common Citizens” and make it easier for them to consume OGD.

In our study, we are particularly interested in those who don’t have skills in data analysis, but have an intention to use and benefit from open data.

Since there are many different groups of consumers and more than a hundred techniques of data visualisation [7], we singled out a group of consumers, defined by Graves et al [4] as common citizens to evaluate three different visualizations. We planned to find out what can make it easier for common citizens to use OGD data. To answer this question we conducted a field experiment in order to empirically evaluate human-usability of OGD visualisations by common citizens with the aim to inform designer and practitioners. In addition we evaluated what stops common citizens to use OGD with the aim to inform OGD community. To conduct field experiment we engaged common citizens in random locations, assigning them only if they had no knowledge in how to create, modify and manage data visualisations.

In Section II, we describe the relationship between data, visualization, and evaluation. In Section III, we explain the methodology used and how it was implemented. In Section IV, we report our results and finding. In Section V, we discuss the results significance and implications; our assumptions and limitations. Section VI describes our conclusions.

II. BACKGROUND

Visualization is an effective technique for communication of data, due to our natural ability to understand patterns [8].

When selecting a visualization technique there are a number of considerations: the underlying scientific principles of human perception and cognition; design guidelines; and the empirical evaluation of the technique.

One challenge with visualization as a science is that it currently does not have a unified general theory [10].

Demiralp [9] identified several causes for a lack of general theory. One issue is that visualization works at several domains in human perception and cognition. Additionally, visualization isn't necessarily limited to what we perceive, but may include an interactive element, which may have a significant impact on the success of the visualization. Demiralp [9] concludes that the question of how to measure and construct effective visualizations in general is an unsolved problem.

In terms of design principles, more work has been done and is somewhat well established. Shneiderman [5] introduced a type-by-task taxonomy to guide designers: overview first; zoom and filter; then details-on-demand [11], which has become the extended principles to guide designers of visualizations.

To judge a particular quality of a system or interface researchers and practitioners use evaluation, which is the last step in the process of the creation of visualizations [12], preferably empirically-driven [13]. Evaluation helps to understand the visualisation tool, visualisations themselves, and the complex process that this tool supports [13], as well as its potential and limitations [6]. This process represents the relationship between data, visualization, and evaluation.

III. METHODOLOGY

To evaluate the usability of open data visualization techniques we performed field experiments using the DataViva [21] open data web portal. DataViva is a web portal for Brazil's open data developed in partnership with the MIT Media Lab. Since starting this study, MIT Media Lab have also launched the Data USA [22] open data portal, which contains updated visualizations. We did not evaluate Data USA in this study.

The field experiment focused on three visualization techniques provided by DataViva: TreeMap, Map, and Stacked. Examples of these visualizations are shown in Figures 1-3.

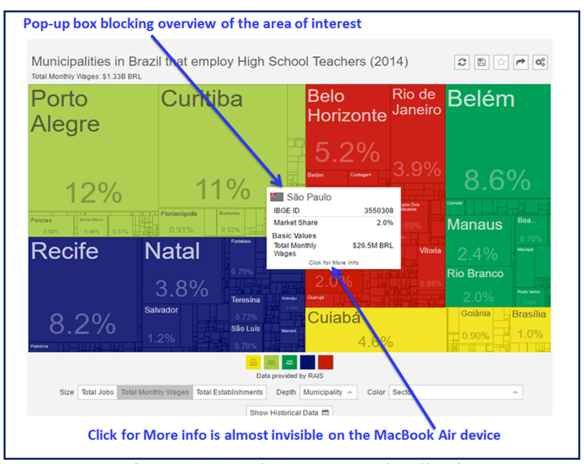

Figure 1. DataViva TreeMap visualization.

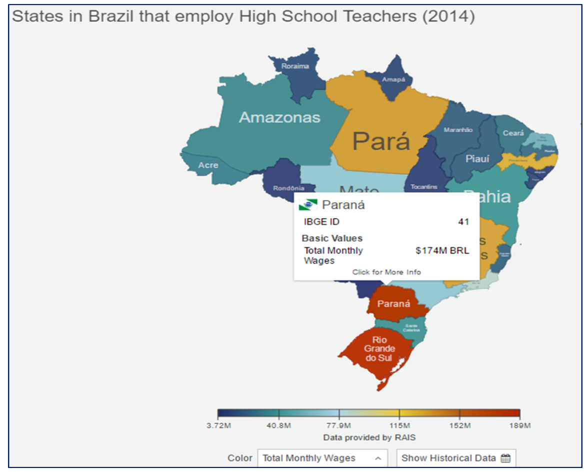

Figure 2. DataViva Map visualization.

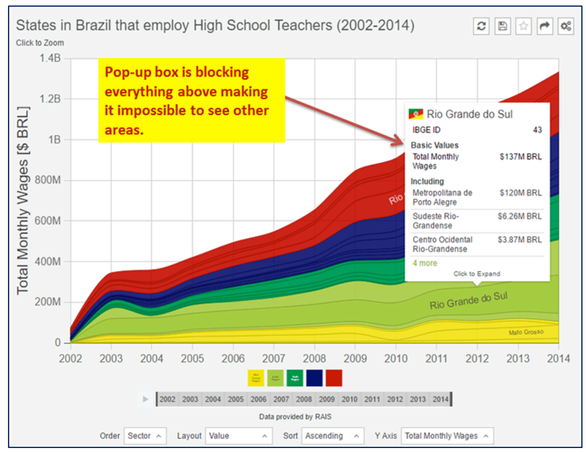

Figure 3. DataViva Stacked visualization.

We engaged our users at 7 different locations around Gold Coast city, Australia, in public places where Wi-Fi access was freely available. To conduct the experiment we used a MacBook Air laptop. DataViva was used to explore simple questions on the Brazilian economy. As a tool for video and audio data collection we used Software Debut.

Our goal was to test at least 10 participants as this is a suitable number according to Faulkner [16].

To balance the control between observer and the users and to balance the trade-offs between generalization, precision, and realism [14], the experiment was broken down into two stages: preliminary stage and controlled-testing stage.

The preliminary stage included presenting the participant with an information sheet about the study and conversational questioning to find out what stops common citizens from using OGD and concluded with the formal signing of the consent form.

The controlled-testing stage included 5 minutes of device and interface familiarization which was followed by performance tasks designed as a motivational scenario based on an envisaged real situation and setting. Tasks were designed to solve real problems with real data. The user's interaction was captured with screen recording software and audio that were later analyzed to calculate completion time. We used an unenforced *think aloud* protocol to support the identification of possible usability issues. Users were given 3 tasks to complete, each using a different visualization technique and a different task for that visualization. The tasks are shown in Table 1.

TABLE 1. VISUALIZATION TASKS COMPLETED BY PARTICIPANTS

Number	Technique	Description
Task 1	TreeMap	How many jobs are in Sao Paulo?
Task 2	Map	What is the nominal wage growth in Sao Paolo?
Task 3	Stacked	What is the total of monthly wages in Sao Paolo?

This was followed by preferential rating to quantify user's opinions for overall assessment of each single visualization interface. Finally, the participants were asked a single open question: Why do you prefer this particular visualization compared to others?

IV. RESULTS

Our experiment sample was based on 12 users. Their average age was 54 years. As shown in Figure 4, 33% had a university degree, 42% had a college education and 25% were educated at TAFE (a technical training institution).

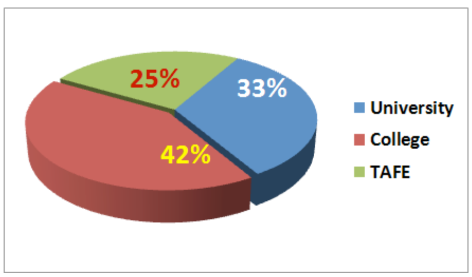

Figure 4. Distribution of participants' occupations.

The time spent per participant to complete the tasks took on average 11 minutes, excluding 5 minutes given to participants to familiarise with the DataViva interface and the time spent to answer an open-ended question.

At the preliminary stage we approached participants with the conversational questioning to find out what stops them from using OGD. 83.2% of participants answered that they had never heard of OGD; did not know OGD existed; or what it means. However, after their interaction with open data, 66.6% had expressed an interest to know more.

The average time to complete each task was calculated and the results are shown in Table 2. The Map visualization was the quickest, followed by Stacked, and then TreeMap.

TABLE 2. CONSISTANCY BETWEEN TIME PERFORMANCE & PREFERABLE CHOICE

Visualizations	Average time per participant	Preferable choice
Map	1 min	First
Stacked	1min 13sec	Second
TreeMap	1min 19sec	Last

Participants were asked to rank the visualizations in order of preference. The participants were asked the question: "What visualization they prefer or perceive as the easiest to use and why?" Figure 5 shows the results of the ranking.

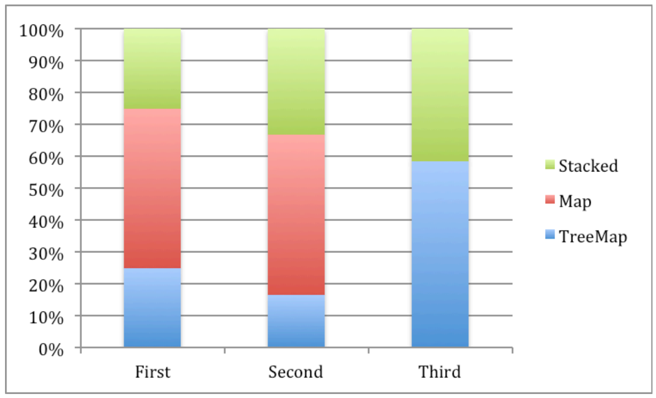

Figure 5. Preferential ranking for each visualization type.

The Map visualization had the most number of first choice rankings, it also had the most number of second choice rankings, and no participants placed it last. The ranking of TreeMap and Stacked were very similar with Stacked having one more ranking in second place and hence one less ranking last. As a result the order of preference for the participants was Map, Stacked, and TreeMap, which correlates with the time it took to complete each task as shown in Table 2.

Participants also provided reasons why they gave visualizations the particular ranking. The Map visualization was chosen because it was perceived as a familiar shape, that of a geographic map, and easy to use.

The Stacked visualisation had contradictory perception. Some perceived it as easy to understand and clear. Others found it confusing and reported that it "didn't make sense".

Participants that rated the TreeMap first found it easy to find information. Those that rated it second stated that it was "not clear". Those that rated it last said it was confusing, busy, and more difficult to find information.

V. DISCUSSION

The field experiments highlighted a number of issues with open data usability. Firstly, only 16.6% of participants had previously heard of open data. Secondly, TreeMap is a very common visualization tool used commonly in data journalism. However, we found that participants had the most trouble with it, both in terms of taking the longest time to complete the task, and also in response to the open question.

The most significant usability problem with all three visualisations was a feature known as the tooltip plugin or more commonly as pop-up box. With all three visualizations, the pop-up box was blocking the overview. Taking into consideration the extended principles for designers of data visualizations: overview first, zoom and filter; then details-on-demand [5] we demonstrated that this feature was blocking overview with details shown in Figures 1-3.

The problem with the feature is that it appears on a mouse rollover. As the user is navigating to interact with the visualization, the popup box occludes the area they want to interact with.

We have provided possible solutions to the popup box issue for each of the visualizations, shown in Figures 6-8. The solution is generally to display the popup box to the side.

Other issues that users reported were difficulty in reading titles or headings or the headings not being visible at all.

VI. CONCLUSIONS

The OGD movement is maturing with large quantities of data being released by governments around the world. The embracing of OGD hasn't necessarily translated into uptake by OGD consumers. We propose that this is because of the focus on machine-readability rather than human-usability. Recent efforts are focusing on providing interactive visualizations of OGD. In this paper, we evaluated one OGD portal to identify strengths and weaknesses between data visualization techniques, specifically for common citizens, which currently hasn't been investigated in the literature.

Even though our participants were unfamiliar with OGD, after a short introduction they were able to answer the problems on average in under 2 minutes, showing the advantage visualizations have over technical and raw data. This serves as a strong argument for OGD portals to provide visualizations to increase end-user uptake by common citizens.

Comparing three different types of visualizations, the clear preference was for Map visualization which presents the data on a geographical map. The basis for Map being the greatest preference both qualitatively and quantitatively is due to its familiarity to the users. Concrete concepts are quicker to grasp than abstract concepts. The TreeMap and Stacked visualizations present data more abstractly and require a greater conceptual leap for common citizens to grasp.

Therefore to encourage end-user uptake of OGD, visualizations should be selected that are concrete and familiar to end-users, such as Map visualizations, and to avoid more abstract visualizations. Note that visualizations such as TreeMap have been designed to address many usability and visualization factors, however, we have found that for common citizens, concreteness and familiarity are more important than other usability factors.

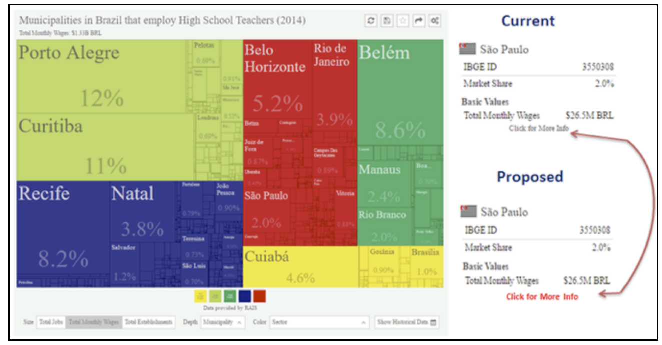

Figure 6. Non-occluding popup box for TreeMap visualization.

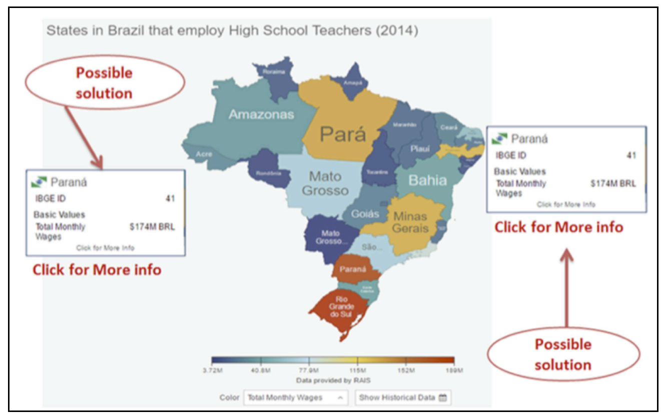

Figure 7. Non-occluding popup box for Map visualization.

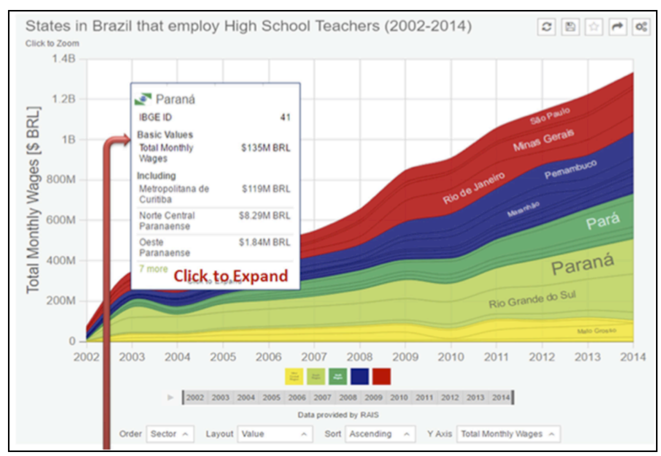

Figure 8. Non-occluding popup box for Stacked visualizaton.

Our study also identified smaller issues such as popups, where a simple and useful feature when poorly implemented can grossly impact the effectiveness of a visualization and reinforces the need not just for visualizations, but for end-user testing to verify the effectiveness of the visualizations.

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Our study compared three visualization techniques. Future work will investigate broader visualization techniques and investigate newer data portals such as Data USA and a new version of DataViva. Additionally more comprehensive tasks can be evaluated that provide greater insights into the strengths and weaknesses of different techniques and enhance the benefits of each.

As Demiralp [9] has identified there is currently no general unified theory of designing and evaluating visualization techniques. We are interested in drawing together the science of perception, design principles, and empirical evaluation to enhance and improve the consumption of OGD.

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