Understanding and Improving Information Extraction From Online Geospatial Data Visualizations for Screen-Reader Users

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COVID-19 Cases per US State
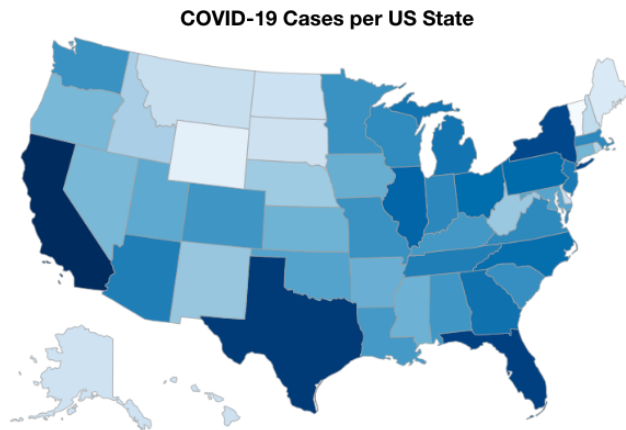
Q: *Tell me the maximum and the average number of cases*

A: **Average cases are 1,514,426.41. Maximum cases are 8,767,944 belonging to California.**

Q: *How is the east coast vs. west coast?*

A: **Average cases for West Coast are 2,256,606.4. Average cases for East Coast is 1,662,346.41. Cases for West Coast are greater than East Coast.**

Q: *Which states are the top 3 and which are the bottom 3 in cases?*

A: **Top 3 states are: California, Texas, Florida. Bottom 3 states are: Vermont, District of Columbia, Wyoming.**

Figure 1: Interactions with a geospatial data visualization showing COVID-19 cases per US state, using our enhancements to VoxLens. "Q" represents questions that screen-reader users can verbally ask using our enhancement, and "A" represents the answers they would hear via their screen readers.

ABSTRACT

Prior work has studied the interaction experiences of screen-reader users with simple online data visualizations (e.g., bar charts, line graphs, scatter plots), highlighting the disenfranchisement of screen-reader users in accessing information from these visualizations. However, the interactions of screen-reader users with online geospatial data visualizations, commonly used by visualization creators to represent geospatial data (e.g., COVID-19 cases per US state),

remain unexplored. In this work, we study the interactions of and information extraction by screen-reader users from online geospatial data visualizations. Specifically, we conducted a user study with 12 screen-reader users to understand the information they seek from online geospatial data visualizations and the questions they ask to extract that information. We utilized our findings to generate a taxonomy of information sought from our participants' interactions. Additionally, we extended the functionalities of VoxLens—an open-source multi-modal solution that improves data visualization accessibility—to enable screen-reader users to extract information from online geospatial data visualizations.

CCS CONCEPTS

• **Human-centered computing** → **Information visualization**; **Accessibility systems and tools**.

KEYWORDS

geospatial, visualization, accessibility, screen reader, blind, voice assistant, map

1 INTRODUCTION

Online data visualizations effectively communicate large volumes of data to their audience [8] and enable users to identify outliers, recognize patterns, and explore oddities in the data that may be challenging to determine from a simple table [25]. The benefits of data visualizations are especially applicable to map-based visualizations that assist users in exploring, summarizing, and analyzing geospatial data [2, 26, 27]. Indeed, geospatial data visualizations displaying information on current events, including COVID-19 cases and vaccination rates per US state and country, were amongst the top 10 most popular interactive data visualizations in 2021 [21, 24].

However, screen-reader users—who may not be able to interact with online visualizations fully using sight—are inherently disenfranchised from extracting information from online visualizations due to the inaccessibility of the visualizations [4, 11, 15, 22]. Several prior works have identified the need for accessible online data visualizations, shedding light on the disenfranchisement caused by inaccessible visualizations for screen-reader users [10, 13, 15, 22, 28]. Most recently, Sharif *et al.* [22] reported that even when an alternative text ("alt-text") exists, screen-reader users spend 211% more time and are 61% less accurate in extracting information from online data visualizations compared to non-screen-reader users. However, their work only explored simple online data visualizations, such as bar charts, line graphs, and scatter plots. We build on their work by understanding interaction experiences and information extraction by screen-reader users from online geospatial data visualizations.

To understand the information screen-reader users seek from online geospatial data visualizations and the questions they ask to extract that information, we conducted a Wizard-of-Oz [3, 6] user study with 12 screen-reader users. We found that our participants grouped and filtered geospatial data through *categorization* and *ranking* in addition to extracting and comparing individual data points. We utilized these findings to develop a taxonomy of information sought by our screen-reader users during their explorations. Finally, using the taxonomy, we extended the functionalities of VoxLens [23]—an open-source JavaScript plug-in that improves the accessibility of online data visualizations using a multi-modal approach—by supporting information extraction from online geospatial data visualizations.

In this work, we contribute the: (1) taxonomy of information sought by our screen-reader users in their explorations of online geospatial data visualizations; and (2) enhancement of VoxLens [23]—an open-source JavaScript plug-in to make online data visualizations accessible—to support information extraction from online geospatial data visualizations.

2 USER STUDY

We conducted a Wizard-of-Oz [3, 6] user study with 12 screen-reader users to understand their information extraction experiences with online geospatial data visualizations, subsequently generating a taxonomy of their interactions. We acted as the "wizards" and simulated responses from a hypothetical screen reader, following recommendations from prior work [9, 12, 16]. We present our methodology, results, and the taxonomy development process.

2.1 Participants, Materials, & Procedure

Our participants were 12 screen-reader users (M=50.3 years, SD=13.6; see Appendix A, Table 2). Seven participants self-identified as women and five as men. We compensated participants with a $20 Amazon gift card for one hour of their time. Our data set included three geospatial data visualizations (curated based on the search results for "most popular map visualizations 2021" on Google): (1) *US traffic congestion in 2021*; (2) *Latest COVID-19 vaccination percentages per country*; and (3) *Percentage of US workers at or below minimum wage in 2021 per state.*

We conducted our studies via Zoom and used its built-in features for recording and transcribing sessions. First, we presented participants with a holistic overview of the visualization generated using VoxLens' *Summary* mode. Then, we asked our participants to explore the data in the visualization by verbally asking questions, replicating the behavior of the *Q-&-A* mode of VoxLens. Each participant interacted with all three visualizations. We randomized the order of the visualizations across participants.

2.2 Analysis & Results

We used semantic thematic analysis [14, 19] and employed Braun and Clarke's "essentialist" method [1], focusing on the "surface meanings of the data." At least two researchers independently coded the transcripts and identified 18 initial thematic codes, resolving our disagreements through mutual discussions. We combined our 18 initial codes into eight axial codes and classified the axial codes into two broader categories. Our inter-rater reliability (IRR), expressed as percentage agreement [7], was 89.4%, demonstrating a high level of agreement between raters [5, 7].

We found that besides extracting and comparing individual data points, our participants performed additional actions in their interactions with online geospatial data visualizations, which we classified into two high-level categories: (1) *Categorization*; and (2) *Ranking*. Specifically, we found that screen-reader users categorize data by (in the order of frequency): *regional, political, climate-related, population-related,* and *spoken-language-related*. For example, P4 inquired about alcohol consumption differences between different regions of Asia: *Are there geographic differences, like, between eastern Asia versus western Asia or southern Asia?* Our participants also ranked data based on their values. Specifically, they sought (in the order of frequency): *top and bottom X data points* and *X data points surrounding the average*; where *X* is an arbitrary number that varied across participants. For example, P3 wanted to find the top three countries in 2021 for COVID-19 vaccination percentages: *So, Hong Kong was the highest, but who is in the second and third position?*

Table 1: Taxonomy of information screen-reader users seek when exploring online geospatial data visualizations to extract and compare data points. Information types within each category are in descending order based on their sought frequency. For each information type, the "Query" column shows some of the questions that our participants asked to extract that information.

Category	Information Type	Query
Categorization	Regional	*Is there a difference between the east and west, or the north and south?*
		Tell me the values of the Southern states as opposed to the Northwest.
	Political	*How do the trends during the Democratic presidential campaigns compare to the trends during Republican presidential campaigns?*
		Do socialist countries have higher rates?
	Climate-Related	*Do warmer climate states have higher values?*
		How are colder places compared to warmer places?
	Population-Related	*Can you compare these two states by population?*
		Do the states with larger population have higher traffic rates?
	Spoken-Language-Related	*Can we compare Spanish speaking countries to the English ones?*
Ranking	Top	*What are the five top countries in Western Europe?*
		I'd like to see them all in order from the highest to the lowest.
	Bottom	*What are the bottom 10 countries in the graph?*
		What about the second and third lowest?
	Surrounding Average	*Which ones are in the middle?*
		What are the three countries that are closest to the average?

2.3 Taxonomy Development

Using these findings, we developed a taxonomy of information sought by screen-reader users containing three tiers: (1) *Category*, the broader categories; (2) *Information Type*, the axial codes; and (3) *Query*, questions that our participants asked to extract a given information type. We show the taxonomy in Table 1, organizing the categories and the information types in the order of their frequency.

3 ENHANCEMENTS TO VOXLENS

Drawing on the results from the taxonomy from our user study with 12 screen-reader users, we extended the capabilities of VoxLens by supporting information extraction from geospatial data visualizations.

3.1 Brief Overview of VoxLens

VoxLens is an open-source JavaScript plug-in that improves the accessibility of online data visualizations for screen-reader users using a multi-modal approach [23], requiring only a single line of code for integration from developers. VoxLens supports three modes: (1) *Q-&-A* (verbal interaction); (2) *Summary* (holistic overview of the data); and (3) *Sonification* (sonified version of the data). However, VoxLens is currently limited to simple visualizations, such as bar charts, line graphs, and scatter plots.

3.2 Our Additions to VoxLens

Our objective was to extend the functionality of VoxLens' *Q-&-A* mode by enabling screen-reader users to extract information from online geospatial data visualizations. To this end, we selected the most frequently sought information types from our taxonomy.

Specifically, we implemented *regional categorization* and ranking the data by the *top*- and *bottom*-most values. To identify the chart type and regional classification to accurately process users' queries, we extended the existing configuration options for developers to include two more parameters: "chartType" and "dataModule." Four values for "chartType" are possible: (1) *bar*; (2) *line*; (3) *scatter*; and (4) *map*. For "dataModule," two values are possible: (1) *state*; and (2) *country*. (No additional data or configuration was required from the developers.)

3.2.1 Regional Categorization. For data involving the states in the US, our participants categorized the data by US regions (e.g., east coast); for countries of the world, they grouped the data by continents (e.g., Asia). Therefore, we implemented two data modules: *state* and *country*. *State* allows the data to be grouped and filtered by US region, whereas *country* does so by continent. Developers can enable regional categorization by using *map* as the "chartType" and specifying the appropriate "dataModule." For example, in a graph representing COVID-19 cases per US state, the user can ask region-related questions, such as: "how is the east coast vs. the west coast?" (Figure 1). We chose the US regions using National Geographic Society's [18] classification of US regions. Additionally, we made our modules scalable, enabling straightforward additions and modifications to the list of our regions.

3.2.2 Support for Ranking. Our enhancements enable the users to obtain the top X and bottom X data points, where X represents any number of data points. For example, users can ask for the top-seven or the bottom-five data points. Our algorithm, currently, only recognizes specific keywords to rank the data (e.g., "top" or "bottom"). We plan on extending the vocabulary in our future iteration.

4 DISCUSSION & CONCLUSION

In this work, we presented a taxonomy of information sought by screen-reader users in their interactions with online geospatial data visualizations, generated using the findings from our user study with 12 screen-reader users. Our work is the first to understand and improve the information extraction of screen-reader users from online geospatial data visualizations. We found that screen-reader users perform regional categorization to extract and compare data points. Additionally, screen-reader users rank the data based on the values of the dependent variable, arranging it by the highest, lowest, and nearest-to-the-average. Utilizing our findings, we extended the capabilities of VoxLens [23], enabling screen-reader users to extract information from online geospatial data visualizations.

In our study, a recurring yet unsurprising observation was that each participant exhibited a distinct way of interacting with online geospatial data visualizations. Although we found high-level similarities in their interactions, their word choices and verbosity levels for the questions they asked to extract information were unique. Therefore, we recommend using personalized designs [17, 20] that cater to the individualized preferences of users by identifying usage patterns (e.g., input queries issued to extract information) to improve the interaction experiences of screen-reader users.

We plan on conducting task-based user studies with screen- and non-screen-reader users to assess the performance of our enhancement to VoxLens using a mixed-methods approach. Additionally, we intend to extend the functionality of VoxLens to include more complex data visualizations, such as multi-line graphs. Future work can employ our methodology to build systems that use voice assistants for screen-reader users to improve their information extraction. We hope that by providing insights into the screen-reader users' interactions with geospatial data visualizations and open-sourcing our code, this work will inspire researchers and developers to make online data visualizations more accessible to screen-reader users and reduce the information access disparity between screen- and non-screen-reader users caused by inaccessible visualizations.

ACKNOWLEDGMENTS

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A PARTICIPANT DEMOGRAPHICS

Table 2: Screen-reader participants, their gender identification, age, screen reader, vision level, and diagnosis. Under the "G" (*Gender*) column, *M = Male*, *F = Female*, and *NB = Non-binary*.

	G	Age	Screen Reader	Vision-Loss Level	Diagnosis
P1	M	36	JAWS	Blind since birth, Complete blindness	Leber Congenital Amaurosis
P2	M	58	JAWS	Complete blindness, Lost vision gradually	Cataracts and Glaucoma
P3	M	49	JAWS	Complete blindness, Lost vision gradually	Leber Congenital Amaurosis
P4	M	32	NVDA	Blind since birth, Complete blindness	Peters Anomaly
P5	F	32	NVDA	Blind since birth, Complete blindness	Retinopathy of Prematurity
P6	F	65	JAWS	Complete blindness, Lost vision gradually	Retinitis Pigmentosa
P7	F	68	Fusion	Lost vision gradually, Partial blindness	Stargaart's Maculopathy
P8	F	69	JAWS	Blind since birth, Complete blindness	Retinopathy of Prematurity
P9	F	52	JAWS	Blind since birth, Complete blindness	Retinopathy of Prematurity
P10	F	38	JAWS	Blind since birth, Complete blindness	Leber Congenital Amaurosis
P11	F	47	JAWS	Complete blindness, Lost vision gradually	Meningitis, Optic Neuropathy
P12	M	57	JAWS	Complete blindness, Lost vision gradually	Retinitis Pigmentosa