Faceted Exploration of Cultural Heritage

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ABSTRACT

The richness of Cultural Heritage (CH) sites exposes tourists to an information overload which makes it difficult to efficiently select the items that they like and can practically visit within a tour.

Faceted information exploration has been proposed as a solution to analyze large sets of data. However, most works focus on the inspection of a single type of information, e.g., hotels or music. In contrast, CH items are heterogeneous: they include natural and artificial monuments and different types of artworks which might be visited within a single tour. Moreover, CH sites are often visited in group, thus raising the expectation that all the involved people share information and decisions about what to do.

In order to address this issue, we propose a map-based faceted exploration model that makes it possible to create custom, long-lasting maps representing a shared information space for user collaboration, and temporally project these maps on the basis of fine-grained filters which help users focus on items associated to short-term, specific interests. Our model supports the user in the organization and filtering of CH information on the basis of multiple perspectives related to the attributes of items. We propose graphical widgets to support interactive data visualization, faceted exploration, category-based information hiding and transparency of results at the same time. The widgets are based on the sunburst diagram, which compactly displays visualization criteria on data categories by showing facets and facet values in a circular structure.

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CCS CONCEPTS

• **Information systems → Web searching and information discovery**; **Search interfaces**; **Geographic information systems**; • **Human-centered computing → Interaction techniques**.

KEYWORDS

Faceted information exploration, interactive user interfaces for CH applications, dynamic projection of geographic maps, Geographic Information search.

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1 INTRODUCTION

In several geographic regions the richness of Cultural Heritage (CH) sites challenges their fruition because it is difficult to identify the interesting items to visit out of the plethora of available ones. While several user-adaptive tour guides have been developed to address this issue (e.g., [7, 10]), they limit the freedom of exploration by only providing the content that is estimated to be relevant to the user. Therefore, they risk to incur into the well-known "bubble effect" [26] affecting recommender systems. The question is thus how to empower users to find relevant information while maintaining them in control of the search process.

Most research on geographic information visualization focuses on helping users retrieve relevant data by leveraging spatial layout to enhance interpretation [39]. However, the existing approaches support an individual user pursuing a short-term information goal; e.g., finding Points of Interest (PoIs) with certain characteristics [22]. Differently, we are interested in using maps as representations of shared data for user collaboration, e.g., in the organization of a tour. In this context, maps have a long-lasting nature, being useful before, during and after the experience. Moreover, they can display heterogeneous data and they might be used by people having different search goals, concerning diverse aspects of items; e.g., not only artistic information, but also geographic and logistic one, such as accessibility information to reach the PoIs. Furthermore, not all the persons traveling together might be interested in exactly the same items, therefore, different visualizations of the set of data relevant to the overall tour are needed. This suggests the creation of custom maps that can be adapted to reflect temporary information goals while persistently storing the shared data in order to preserve the overall collaboration context.

In this work we propose a faceted information exploration model [14] that supports dynamic map projection over multiple data categories without loss of content. The projection is at two granularity levels: a coarse-grained one supports general category hiding, and a fine-grained one helps selecting the items to be visualized within a specific category. Our model supports interactive data visualization, faceted exploration, category-based information hiding and transparency of results. The model is implemented by means of a widget that compactly displays the visualization criteria applied to a data category by showing facets and facet values in a circular structure (a sunburst diagram) which supports a concise representation of the search context. The widget also includes a transparency slider useful to focus maps on specific data categories without specifying detailed facet-based visualization constraints. We carried out a preliminary user study to test our model. This study has shown that, when working on geographic maps populated with multiple data categories, our model outperforms in user performance and experience the traditional approaches based on checkboxes. In summary, this paper provides the following contributions:

- Dynamic map projection over multiple data categories without loss of content.
- Visual representation of searched data categories as compact graphical widgets supporting interactive data visualization, faceted exploration, category-based information hiding and transparency of results.

The remainder of this paper is organized as follows: Section 2 describes the related work and Section 3 presents our model. Section 4 summarizes the user study we carried out and the emerging findings. Section 5 concludes the paper.

2 RESEARCH ABOUT FACETED INFORMATION EXPLORATION

Building on Ahlberg and Shneiderman's seminal work [2], the faceted search model [14, 35] uses dynamic filters to help the user identify relevant terms for information filtering. Different types of filters are used; e.g., keywords or terms extracted from textual queries and concepts extracted from a document pool [16], or attributes of Linked Data [15]. Moreover, facets can be shown according to various visualization models; e.g., FacetLens [19] displays clickable facets in matrix-based bubbles, each one associated with a search filter; moreover, FacetZoom [13] proposes a stack-based visualization of hierarchical facets. SearchLens [9] enables users to define reusable composite facet specifications (lenses) to support information filtering based on soft constraints. In order to support the faceted exploration of semantic data [40], Hippalus [32] introduces the Faceted and Dynamic Taxonomies to manage both hard and soft constraints and PFSgeo [22] extends Hippalus to geographic information management.

While most of these works focus on a single data type, our map projection approach enables users to work with multiple data categories and to focus the map on temporary information goals without losing data, in support of long-lasting activities. However, we currently only manage strict visualization constraints.

Several works go beyond the traditional ranked list to support visual thinking about search results [21]. HotMap and Concept Highlighter [16] adopt color coding to visualize, for each retrieved document, a keyword-based or semantic degree of match with the search query. Exploration Wall [17] provides streams of topically related results and it prompts suggestions to help information search on mobile devices. SearchLens [9] enriches the ranked list with a detailed specification of the degree of match between each retrieved item and the lenses selected by the user. Other models adopt 2D or 3D representations; e.g., VIBE [27] presents data on a 2D plane using proximity to denote content similarity with respect to Points of Interest in the map, which denote particularly interesting keywords or topics. Cartograph [36] uses thematic cartography to visually represent semantic relations among non geographic results. Descartes [3] leverages cartographic knowledge to generate expressive maps on the basis of the type of geo-data to be shown.

As the geographic dimension of POIs is of primary importance in our work, we overlay them on a geographic map. However, we adopt color coding to consistently represent the widget of a data category, the visualization constraints expressed by the user and the items of the category displayed in the map.

Recent work on hybrid recommender systems [34] employs graphical visualization to enhance their transparency. The recommenders are mapped to facets and the user can specify their weight in the generation of recommendations. Systems differ in the visualization of results; e.g., similar to our model, MyMovieFinder [24] adopts a ranked-list visualization and, by clicking on items, the user can see the recommendation criteria they meet. Moreover, IntersectionExplorer [8] uses the UpSet matrix [20] to visualize the number of common suggestions provided by the recommenders.

The UpSet matrix is an interesting explanation tool for faceted search that we could apply to each data category selected by the user. However, geo-data may have a large number of facets, increasing the size of the matrices. Therefore, the benefit of a detailed matrix-based analysis of results should be investigated.

3 INFORMATION EXPLORATION MODEL

Our model is integrated in the OnToMap [5, 6] Web collaborative GIS, which supports the management of custom maps for information sharing and participatory decision-making and is exploited as data container in the "co3project: co-create, co-produce, co-manage" [11]. OnToMap uses a semantic representation of domain knowledge based on an OWL [31] ontology that defines data categories and facets. This ontology is mapped to the domain representations of external data sources in order to retrieve information from them. The ontology also specifies graphical details for map visualization;

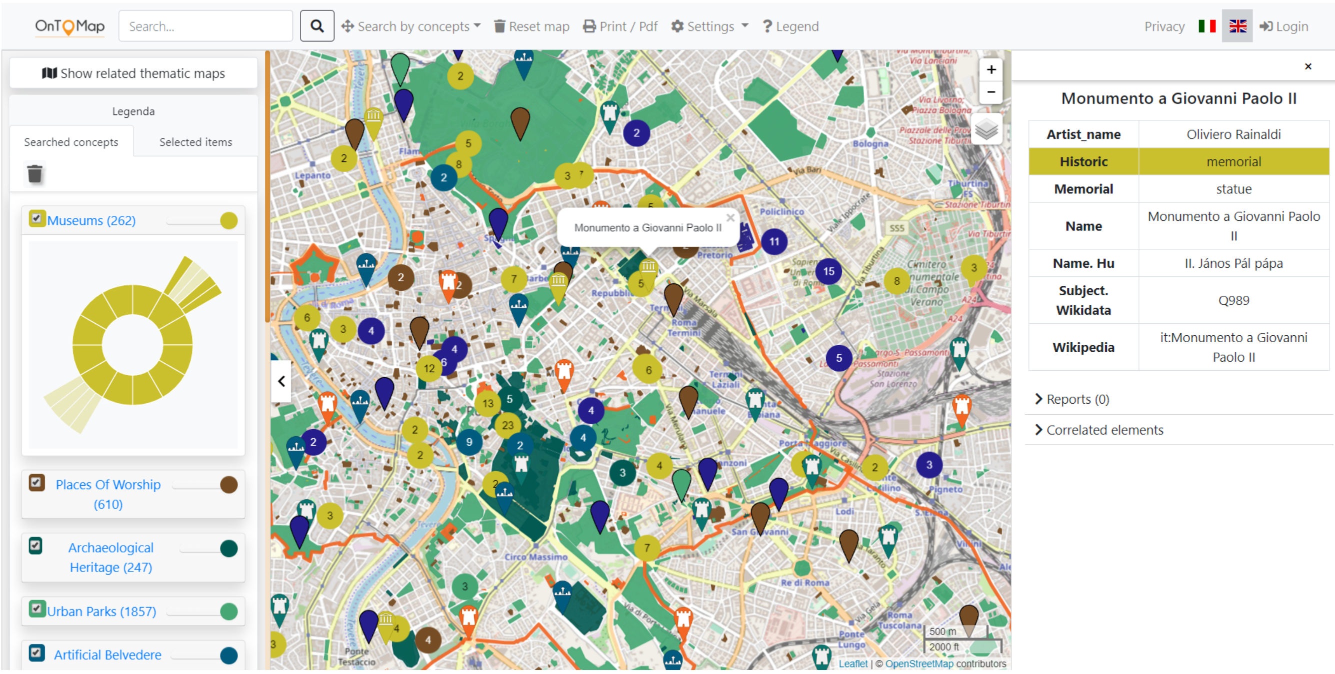

Figure 1: OnToMap user interface showing the widgets based on sunburst and the details of a POI ("Monumento a Giovanni Paolo II" - monument to Giovanni Paolo II). Data retrieved from OpenStreetMap; see Footnote 1.

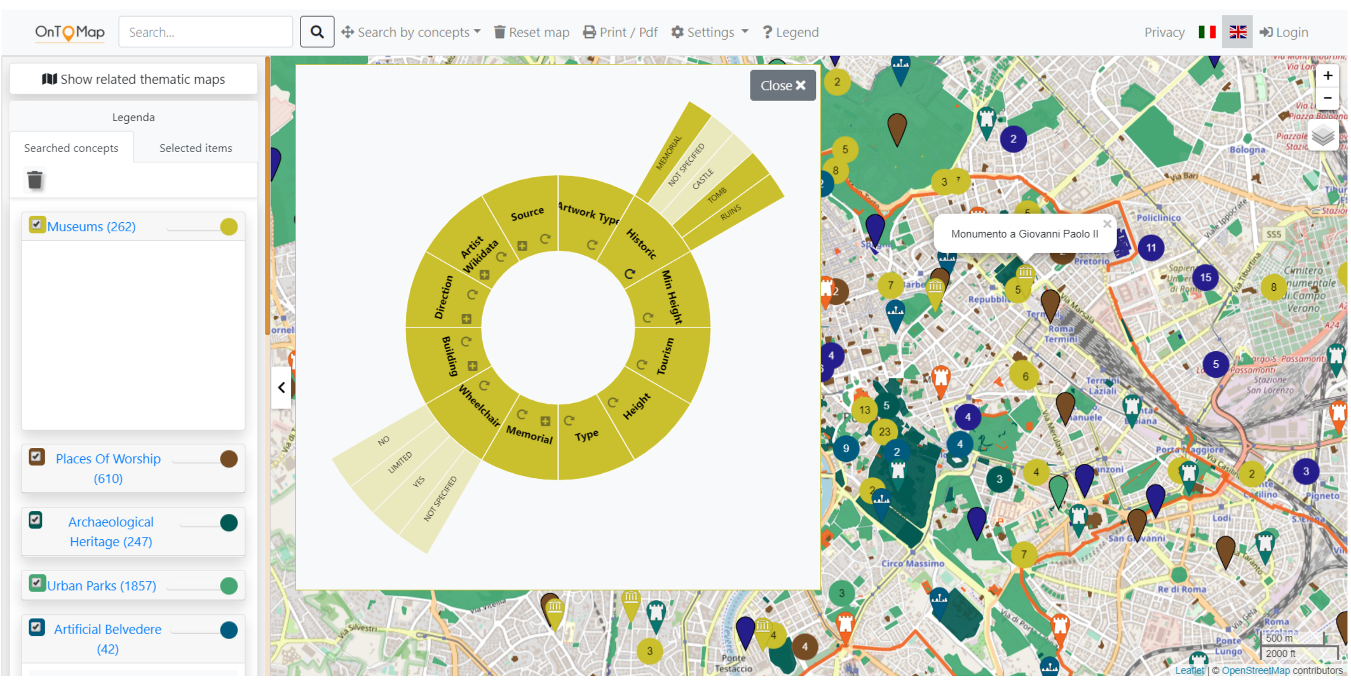

Figure 2: Expansion of the "Museums" widget to view its facets and selected values in detail. Data retrieved from OpenStreetMap; see Footnote 1.

e.g., category color and icon. The current implementation of the system retrieves data from OpenStreetMap [28].[1]

[1]The data visualized in the figures of this paper has been retrieved from OpenStreetMap on February 8th, 2020.

Figure 1 shows the user interface of OnToMap. The top bar wraps the control panel that supports free-text search ("Search..."), category browsing ("Browse by concepts"), tools for printing the map, choosing visualization settings and logging in, and map management for authenticated users. The right panel contains the map, which displays information items as pointers or as geometries, depending on the available data. The user can inspect the details of each item x by clicking on its pointer; in turn, the system generates a table describing the details of x; e.g., see the table of item "Monumento a Giovanni Paolo II" in the right portion of the figure. Color coding connects widgets to items and to clusters of items in the map. The left side bar shows the search context by displaying a widget for each data category searched by the user during the interaction with the system.

3.1 Category widgets

The widgets representing the data categories searched by the user are the key tools to explore the results and to focus the map on the basis of temporary information needs. Specifically, the widget associated to a data category C includes two components:

- The first one is a transparency slider that was introduced in [4] to support map focusing via opacity tuning. By moving the slider, the user can change the opacity level of all the items belonging to C. This is inspired by pioneer work on layers visualization [12] but it works at the granularity level of the represented category. The transparency slider also supports the visualization of multiple layers, as a generalization of Translucent Overlay [23].
- The second component is a sunburst diagram supporting the specification of facet-based visualization constraints on the retrieved items of C. This component shows facets in a ring colored as the represented category; e.g., see the right portion of Figure 2. The user can view facet values by clicking on the slices of the ring. Values are sorted clockwise by decreasing frequency order (the number of items can be viewed on mouse over) and they are displayed in a pale tone of the color of the category. The less frequent facet values are available on demand by clicking on the "+" buttons associated to each facet. By clicking on a value, the user applies it as a visualization criterion for the selection of the information items to be displayed in the map, and the component takes the color of the category; e.g., in the figure the user has selected values "MEMORIAL", "TOMB" and "RUINS" of facet "Historic".

The side bar of the user interface shows widgets as thumbnails that can be expanded in a pop-up window to view their details. The user can close or expand each widget by clicking on its box; moreover, it can minimize widgets to only visualize the transparency sliders. For instance, in Figure 1 "Places of Worship", "Archeological Heritage" and "Urban Parks" are minimized while "Museums" is closed but not minimized. Differently, in Figure 2 the "Museums" widget is expanded and shows the facets of this category and the values selected by the user to visualize map content.

It can be noticed that the selection of multiple values of the same facet represents an OR visualization constraint. This means that the items having any of the selected values are eligible for visualization. Differently, the selection of values belonging to different facets is an AND constraint because it requires that items have the specified values for all these facets.

3.2 Selection of facets within a widget

The number of facets associated to a specific data category depends on the richness of its metadata and can be rather high. For instance, most OpenStreetMap categories have hundreds of tags which correspond to candidate facets for information exploration. However, not all of these tags are equally useful: some of them are rarely used; other ones represent identifiers and thus fail to support item selection in large sets because they would lead to explore the sets item by item.

Given a category C, we select the facets to be displayed in a widget on the basis of how efficiently their values support the exploration of the retrieved items of C, henceforth denoted as E_C, i.e., extension of C. Specifically, we select up to a maximum of 14 facets, which is suitable for visualization in the sunburst diagram, by applying the following strategy:

(1) We first filter out the facets missing in most of the items of E_C in order to avoid proposing visualization criteria that can be applied to very few items. This is a real risk when using crowdsourced information; for OpenStreetMap data we set the minimum threshold for the visualization of facets to 3%.
(2) We then compute the *cost of exploring* E_C by using each of the remaining facets and we include in the widget those having low (but not null, see below) cost because they support the most efficient exploration of the set.

In [29] Oren et al. propose balance as a main criterion for computing the efficiency of facets, considering that if a facet splits a set in subsets having uniform cardinality, then the user can reduce the search space in a low number of steps. Differently, we privilege facets having a low number of values and/or splitting E_C in some large subsets. The reason is that, in crowdsourced datasets, users tend to define many different tags, most of which are hardly used; e.g., see [30]. Thus, it is important to identify the tags that split the result set in a low number of (possibly unbalanced) large subsets: in that way the system can propose visualization criteria that enable a significant reduction of the search space. In order to capture this logic, we compute the cost of exploring E_C by means of a facet f_i as the ratio between the entropy of f_i and the mean frequency of the values of f_i in E_C:

$$cost(f_i) = \frac{-\sum_{j=1}^{m} p(v_{ij}) log_2 p(v_{ij})}{meanFr(f_i)} \qquad (1)$$

where

- $p(v_{ij})$ is the probability of v_{ij} in E_C, considering the values $v_{ij} \neq$ "NOT SPECIFIED"; i.e., only the items having the facet.
- $meanFr(f_i) = \frac{|E_C|}{m}$. The mean frequency describes the average cardinality of the subsets identified by the facet.

As the entropy of f_i is positively influenced by the balance of the subsets of E_C identified by f_i and by the number of values of f_i, the numerator of Equation 1 takes higher values when facets have many different values. At the same time, if the mean cardinality of the subsets in which the facet splits the result set is large, the denominator of the equation dramatically reduces the cost, so that exploring the set using the facet is considered as convenient. Notice that a facet representing an identifier is evaluated as highly costly

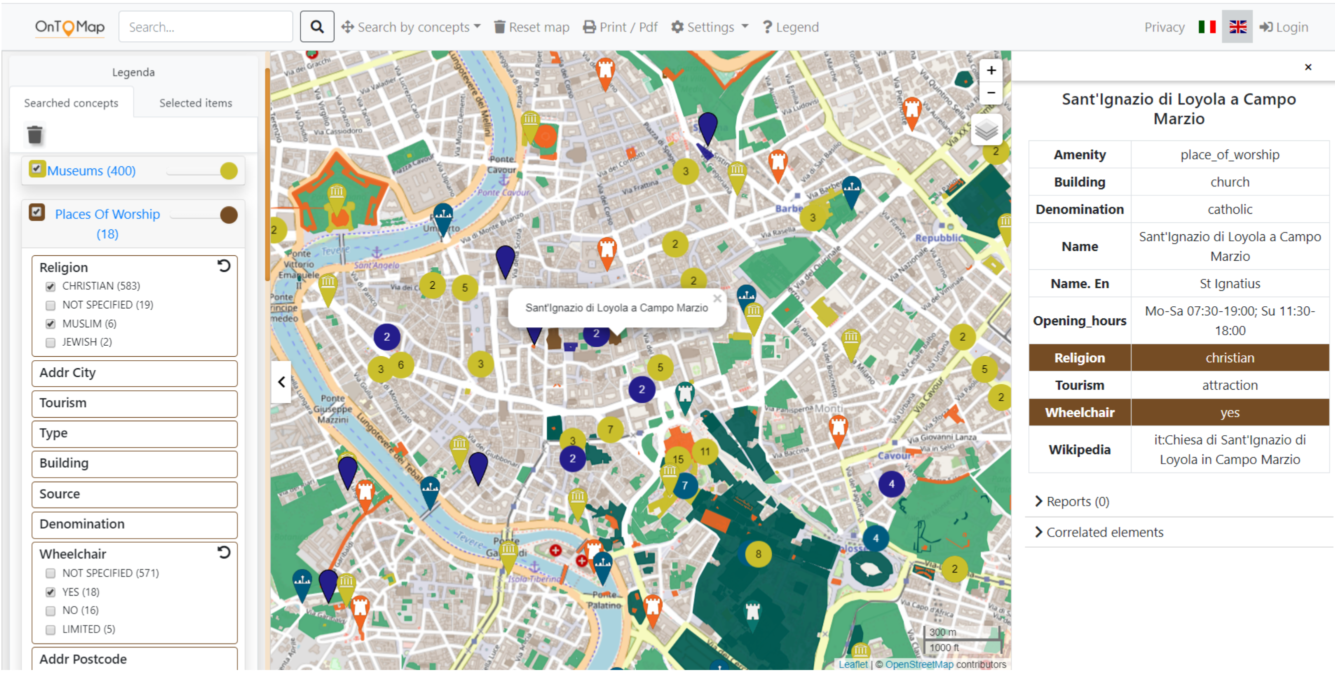

Figure 3: OnToMap user interface showing the widgets based on the checkboxes. Data retrieved from OpenStreetMap; see Footnote 1.

if it has a high number of different values because they should be considered one by one to inspect the results.

Given the cost of facets, we select the most useful ones by sorting them in increasing order of cost. However we exclude those such that $cost(f_i) = 0$ because they have a single value in E_C and thus they fail to split the set.

4 VALIDATION OF OUR MODEL

We conducted a preliminary user study to compare the helpfulness of the widgets in the exploration of an information space via map projection. We were interested in comparing the performance of our faceted information exploration model, based on the sunburst widget, to a standard model based on checkboxes, as these are largely used in online services. For this purpose we also implemented a version of the side bar of OnToMap that uses checkboxes instead of sunburst diagrams as widgets; see Figure 3.

We involved in the study some students and people working in the university or in the industry and we asked them to carry out two map learning tasks, using checkboxes and sunburst respectively. We prepared in advance two maps populated with multiple data categories to simulate a tour planning context. For each task the participant had to look at the associated map and (s)he was asked to answer two questions which required counting elements that have certain properties, or identifying items given their descriptions, within a restricted area identified by means of an orange line. The questions proposed to the participants have the following templates:

(a) How many *category name* having $characteristic_1$ and/or …and/or $characteristic_n$ are visualized within the area delimited by the orange line in the map?
For instance, "How many Muslim churches accessible to wheelchairs are visualized within the area delimited by the orange line in the map?"

(b) Find *category name* having $characteristic_1$ and/or …and/or $characteristic_n$ within the orange line in the map, and list them.
For example, find restaurants serving pizza or Italian food (values of facet "Cuisine").

We asked rather selective questions because we wanted to understand whether the widgets helped participants satisfy specific information needs by exploring the metadata of the searched categories and by projecting the maps accordingly. We organized the analysis as follows:

- As objective performance indicators we measured task completion time and the percentage of correctly answered questions.
- As a subjective measure we analyzed user experience:
  - After each task, participants filled in a post-task questionnaire to evaluate the type of widget they had just used.
  - After the completion of the two tasks they filled in a post-test questionnaire to compare the two types of widgets.

  In these questionnaires we asked participants to evaluate the perceived easy of use, novelty and efficacy of the widgets in supporting map interpretation.

Our preliminary experiment provided encouraging results:

- As far as performance is concerned, participants correctly answered all the questions, using any widget. However they worked faster when they used the sunburst; this finding provides evidence about the efficacy of this widget.

- Regarding user experience, participants perceived both widgets as helpful and moderately effort saving. They considered the widget based on the checkboxes as the easiest tool and the sunburst as the most novel one. In spite of the initial difficulties in using the sunburst, they evaluated it as a good model to compactly visualize all the facets and values of a data category. They also appreciated the fact that, being compact, the sunburst minimizes the vertical expansion of the side bar: with respect to the checkboxes, it reduces the need to scroll the bar in order to visualize the other widgets of interest. This helps the identification of the information needed to carry out the tasks of the experiment. Participants also declared that the sunburst helped question answering in an efficacious way.

An interesting result we obtained both while watching participants' behavior and from the open questions they answered in the post-test is that, regardless of the type of widget, participants found it convenient to organize search in two phases:

(1) Visual simplification of the maps by hiding the data categories that are irrelevant to the questions to be answered, using transparency sliders.
(2) Identification of the items of the category of interest on the basis of their properties by means of faceted exploration.

Overall, these results suggest that the graphical compactness of widgets is important in data exploration when the maps are populated with diverse types of information. Results also show that users appreciate the combination of coarse-grained information hiding (transparency sliders) with fine-grained faceted selection (checkboxes or sunburst) in the widget, so that they can first reduce the complexity of the map, and then focus on the details of the categories of interest.

These results are confirmed by a more extensive evaluation of our faceted exploration model, where we compared the widgets based on sunburst with further types of widgets and on a larger user base; see [25] for details.

5 CONCLUSIONS

We presented a faceted-exploration model supporting dynamic map projection to help the analysis of heterogeneous geographic information. Our model is based on interactive widgets which support information exploration at two granularity levels, i.e., by projecting a map on specific data categories and/or according to specific attributes of items. As such, our model is particularly suitable for the presentation and exploration of Cultural Heritage data, which is characterized by rather different search dimensions, including geographic, artistic and logistic aspects such as wheelchair accessibility. All these dimensions deeply influence the relevance of items to the individual user.

We carried out a preliminary user test to evaluate users' performance and experience with our model by considering two user interfaces: in the former, interactive widgets for faceted exploration are based on the sunburst diagram, which supports a compact visualization of data facets and values. In the latter, the sunburst diagram is replaced by traditional checkboxes for facet value selection. The evaluation results, extended in [25], suggest that the type of map projection we propose, based on two granularity levels for information exploration, is useful when exploring heterogeneous map-based information. Moreover, they show that the sunburst diagram is more efficacious than the checkboxes used by most online services in supporting information exploration.

Our future work aims at extending our facet-based model in order to take individual and group-based user's information needs into account. Specifically:

- Currently, our model supports a "one size fits all" type of faceted search that exploits general efficiency criteria to guide the user in data exploration. However, some researchers propose to adapt facet suggestion to the user's preferences in order to personalize the navigation of the information space; e.g., see [1, 18, 37, 38]. In our future work, we plan to offer multiple data exploration strategies which the user can choose from, including a user-adaptive facet suggestion that depends on her/his preferences and on the search context.
- The OnToMap user interface enables multiple users to view the same shared map by applying parallel visualization constraints; i.e., given the selected categories of information, each user can focus on the data (s)he is most interested in. However, it is interesting to explore the synchronization of visualizations among users, in order to support collaborative work "in synch". We will investigate this aspect in further experiments.
- Depending on their roles, in some scenarios users might need to access different, long-lasting custom views of a shared information space [33]. We plan to extend our model by introducing permanent, user-dependent views on map content.

Our future work also includes the organization of experiments to evaluate the efficacy of our model in mobile settings and, possibly, using small displays such as those of mobile phones. This is important to check whether our approach successfully supports people while visiting physical CH places. At the current stage, we only tested the suitability of the model in a planning scenario.

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