TopoGroups: Context-Preserving Visual Illustration of Multi-Scale Spatial Aggregates

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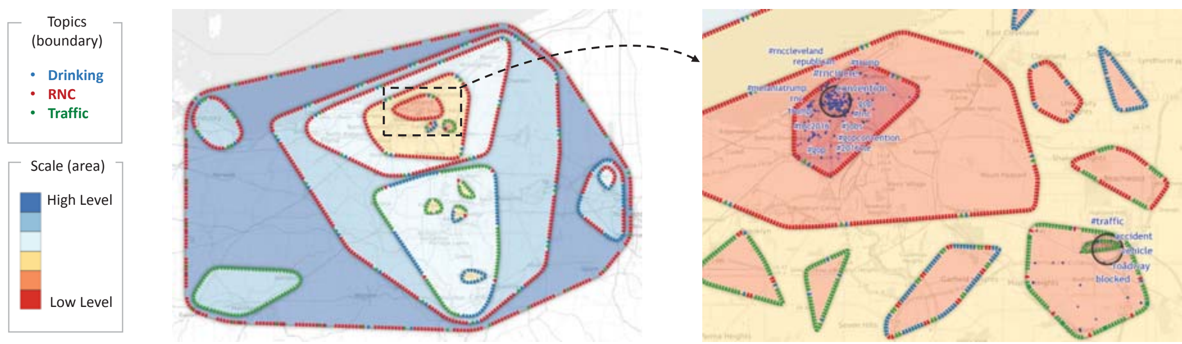

Figure 1. The TopoGroups technique showing multiple levels of spatial aggregation of social media posts around Cleveland, OH, during the 2016 Republican National Convention. TopoGroups supports effective comparison, correlation and analysis of multi-scale aggregates by combining them into the same display, thereby helping users to understand the spatial distribution as well as identify trends and anomalies at different granularity levels.

ABSTRACT
Spatial datasets, such as tweets in a geographic area, often exhibit different distribution patterns at multiple levels of scale, such as live updates about events occurring in very specific locations on the map. Navigating in such multi-scale data-rich spaces is often inefficient, requires users to choose between overview or detail information, and does not support identifying spatial patterns at varying scales. In this paper, we propose TopoGroups, a novel context-preserving technique that aggregates spatial data into hierarchical clusters to improve exploration and navigation at multiple spatial scales. The technique uses a boundary distortion algorithm to minimize the visual clutter caused by overlapping aggregates. Our user study explores multiple visual encoding strategies for TopoGroups including color, transparency, shading, and shapes in order to convey the hierarchical and statistical information of the geographical aggregates at different scales.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

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Context preservation; social media; multi-scale analysis; geospatial visualization.

INTRODUCTION
In geography, Tobler [35] tells us that *"everything is related to everything else, but near things are more related than distant things."* Practically speaking, this means that spatial datasets—such as geotagged tweets in an area, weather station measurements across a region, or Yelp reviews for tourist spots in a city—often exhibit different patterns at multiple different levels of scale. For example, while tweets in a particular city may be dominated by the visit of a foreign dignitary (say, the Pope visiting Philadelphia in September 2015; `#popeinphilly`), there may be other, more local patterns in the same geographic region (such as a Black Lives Matter protest in the same city; `#BLM`). Using traditional visualization approaches to navigate such geospatial datasets often causes global patterns to overshadow local ones, can be tedious and inefficient [24], and does not provide an overview when focusing on specific details (and vice versa). What's more, choosing the proper scale and interpreting the results become non-trivial tasks [28].

We propose TopoGroups, a multi-scale visual analytics technique based on automatic hierarchical spatial clustering of data. TopoGroups models multi-scale spatial clusters as a hierarchical tree structure where each node in the tree represents a specific cluster, and each edge indicates a parent-child relationship of clusters at adjacent scales. The technique visualizes multiple levels of the hierarchy at the same time to provide information about patterns at multiple scales of aggregation (Figure 1). The boundary of each cluster is modeled using an implicit curve that is distorted to reduce overlap between clusters at adjacent scales. The TopoGroups technique also allows for coupling navigation to the visual representation; double-clicking on a specific cluster automatically zooms and pans the viewport to fit the entire viewport to its extents.

The design space of the TopoGroups technique includes multiple visual encoding choices using color, transparency, shading, and shape for representing aggregation level, cluster contents, and statistical aspects of the spatial data. To determine the strengths and weaknesses of each visual encoding strategy, we conducted several controlled laboratory experiments where participants are asked to perform spatial analysis tasks under different visual encodings. Our results yield guidelines on which visual encodings to use depending on the user, task, and application. We also discuss ideas for how TopoGroups can be extended with text visualization encoding to show terms, phrases, and topics for each cluster. The practical applications for TopoGroups include geographic information systems (GIS), geospatial visual analytics, and online geographic services such as Google Maps, Bing Maps, and OpenStreetMap.

BACKGROUND

To facilitate effective exploration of geospatial datasets at multiple spatial scales, researchers in the visual analysis field have proposed various visual and interaction methods. Below we discuss work related to multi-scale interactive navigation, multi-scale visual summary, and context-preserving design.

Multi-Scale Navigation

Interactive maps allow users to explore geospatial datasets at multiple scales by directly zooming in and out of a region of interest. Although this technique has been applied in various visual analytics frameworks [4, 29, 5], there exists several limitations: First, users need to switch between different spatial scales in order to observe the corresponding results, which adds heavy interaction overload. Moreover, since the map typically only visualizes the results at the current scale, users can easily lose the semantic context of the previous scales as they interact across multiple scales.

In order to reduce the interaction overload and maintain the semantic context, researchers have proposed several frameworks that juxtapose multiple maps at different scales, which allow users to visually compare the multi-scale analysis results without the need to perform numerous zooming operations. Ferreira et al. [14] develop an interactive system to visualize spatiotemporal distributions of birds. Their system provides multiple coordinated geographical map views to facilitate the effective visual comparison of different spatial regions across multiple scales. Javed et al. [23] propose a novel visual design named stack zooming. As users navigate on the map from higher to lower scales, the corresponding geographical views stack on each other in order to indicate the hierarchical relationships across multiple scales. Delort [9] establishes a hierarchical tree based on the spatial clustering results that enables users to interactively select different cluster nodes at different scales and visualizes the clusters using a Voronoi partition. Zhang et al. [42] propose a two-staged animated transition technique in order to provide a smooth visual transition as users navigate through multiple spatial scales.

Similarly to the juxtaposition approach, our method aims to summarize multi-scale visual results in a single, compact visualization to reduce the interaction overload and further facilitate effective correlation and analysis across different scales.

Multi-Scale Visual Summary

Besides the aforementioned interaction-based approaches, there also exist visual approaches that create summaries of the analysis results at multiple scales in a single visualization. This approach effectively maintains the context of exploration and reduces the overload caused by jumping across different views for visual comparison. Dykes and Brunsdon [11] use multiple line charts to encode the relationships between the statistical results and the geographical scales. Turkay et al. [37] propose *attribute signature*, which summarizes the multi-scale statistical results in a static visualization that avoids the tedious zooming operations and meanwhile maintains the context of different scales. Goodwin et al. [18] propose a novel glyph design named *Scale Mosaic*, in which they use a set of concentric rectangular rings to encode the correlations of the statistical variables from global to local scales.

Although these solutions manage to facilitate effective multi-scale analysis and context preservation, most of them are oriented toward statistical analysis (such as correlation analysis) of multivariate geographical data, where the analysis result at one scale can be represented as numeric values. In contrast, our work aim to provide a visual summary of multi-scale spatial clusters. To the best of our knowledge, little work has been done in the visual analytics field to focus on combining the multi-scale spatial aggregates in the same visual space.

Context-Preserving Visual Design

Overview+Detail and Focus+Context techniques [6] have been widely applied in the visualization field to provide efficient context preservation. Overview+detail separates the focus and context into separate views, while focus+context seamlessly integrates the focus within the context, often by applying distortion such as fisheye distortion [16, 17]. For overview+detail, the stack zooming technique [21] has been applied to both time-series exploration as well as geographical navigation [23]. In terms of focus+context, Gutwin [19] improves fisheye views by dynamically adjusting the distortion effect based on the movement of the cursor to allow users to more effectively target objects. Pietriga and Appert [30] explore several dimensions including transparency and time to control the transition between the context of focus. Variants of fisheye techniques have been applied to various usage scenarios, such as the system diagrams [7, 40], word cloud layout [8], and road visualization [33]. Other related examples can be found in the survey paper by Tominski et al. [36].

Similar to focus+context, our approach combines the visualization of different scales in the same display. We design an overlap minimization method that distorts the contour of spatial clusters to reduce visual clutter, making it easier for users to identify aggregates at different scales.

Figure 2. Examples of multi-scale clustering: (a) Keywords are aggregated and displayed on the map (Tag Map). Zooming into the map shows lower-level sub-events [34]; (b) Spatial clusters are visualized at consecutive zoom levels. Large clusters at a higher zoom level split into multiple small ones at a lower level [42]; (c) Clustering results of demographic statistics under different geographical resolutions (left: state level, right: county level) [43].

CHALLENGES AND TASK CHARACTERIZATION

Spatial clustering is an important component within spatial data mining [2], which generally refers to approaches that groups spatial data points into classes based on their spatial proximity. Spatial clustering provides valuable insights into the spatial data distribution, characteristics of the individual groups, as well as trends and anomalies within the dataset. Creating these clusters and exploring their characteristics across multiple spatial scales is an important but challenging task.

Varying scale is an inherent property in multi-scale data analysis and spatial clustering analysis (e.g., [3, 28, 22, 25]). Spatial datasets can be aggregated by varying granularity levels that are determined by a distance measure between pairwise data points in the clustering process. Accordingly, clustering results often vary significantly across different scales, as Figure 2 shows. Although the variation in scale provides a unique perspective to characterize the spatial data attributes [28], compared to a single scale, the size of analysis space in the multi-scale scenario exhibits an approximate quadratic growth. Moreover, navigating and correlating across scales remains a non-trivial task to domain experts in various fields where multi-scale analysis is critical in their domain-specific tasks. The challenges faced can be characterized into two major aspects, **interaction overload** and **cognitive overload**.

Spatial scales typically range from an overview (the global view) to low level details (individual data points). From the global perspective, the entire dataset is aggregated as a single object, which may provide overall summary information, but is too coarse-grained to reveal potential spatial patterns. From the detail perspective, each individual data point is regarded as one cluster, where no actual aggregation exists for analysis. Therefore, users have to identify the appropriate scales between these polar extremes that can best characterize the hidden spatial patterns. Conventional navigation paradigms such as the zooming operation require the users to switch to each individual scale in order to understand the analysis result at that scale, adding significant **interaction overload** to the analysis process. Moreover, in most multi-scale analysis scenarios, understanding how the spatial attributes and patterns evolve across scales is critical. For example, crime in certain regions may be unnaturally high; however, this may be explained if local geospatial patterns (e.g., petty thefts at the mall) are analyzed. Hence, users require the ability to effectively correlate analytical results between different scales. With conventional navigation paradigms, users have to remember the analysis result at different scales during the navigation and mentally correlating those results further increases their **cognitive overload** in the analysis process.

We characterize a set of representative analytical tasks that are involved in the navigation and exploration of multi-scale spatial aggregates [1, 27, 31, 32]. The task characterization guides the design of our context-preserving technique and provides motivation for research in similar areas.

- T1 Establish an overview of the geographical distribution of aggregates at multiple scales.
- T2 Distinguish different aggregates at the same and/or across different scales in the geographical space and identify their potential relationships.
- T3 Locate aggregates of interest at the same and/or across different scales. Determine the spatial extent of the aggregates.
- T4 Measure and compare the volume of domain-specific attributes for the aggregates at the same and/or across scales.
- T5 Access raw data items (e.g., geographical location, domain attributes) associated with a specific aggregate on demand.

TOPOGROUPS: MULTI-SCALE SPATIAL AGGREGATES

In order to tackle the aforementioned challenges, we propose TopoGroups, a visual analytics approach that enables effective context-preserving navigation and exploration of spatial clusters at multiple scales. Motivated by past work [18, 37, 39], TopoGroups aims to superimpose clusters of multiple scales into a single visual display (T1, T2, T3, T4). With such a design, the user can easily understand the structure of the space at several levels of scale, reducing **cognitive load**. Furthermore, this also minimizes the need for navigating across multiple scales, thus reducing **interaction overload** as well.

TopoGroups consists of two major steps, following the hierarchical aggregation model proposed by Elmqvist and Fekete [12]. First, we model the multi-scale spatial clusters as a hierarchical representation where each scale (zoom level) maps to a specific layer in the hierarchical structure. This step has been described as *data space aggregation* [12]. Second, we design our visual interface that allows users to explore the spatial clusters both hierarchically and spatially, while maintaining the context of navigation at different spatial scales. This step has been described as *simplified visual representations of the aggregates in visual space* [12].

Generating the Spatial Aggregate Hierarchy

Geospatial datasets are typically represented by latitude and longitude in a geographical coordinate system, and can be transformed into planar coordinates based on map projection

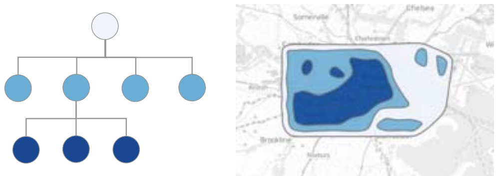


Figure 3. The hierarchical (left) and the corresponding geospatial (right) representations of the multi-scale aggregates

methods. In TopoGroups, the geo-spatial data points are projected into 2D screen space coordinates, where the clustering is performed. TopoGroups utilizes the common algorithm where each data point only belongs to one cluster at a single scale (e.g., the DBSCAN [13] algorithm). We also note that the clustering process maintains a consistent distance measure (Euclidean distance in screen space) across different spatial scales (zoom level). Under such conditions, geospatial data clustering highly depends on the spatial scales (zoom levels) of the geographical space. As the spatial scale varies from a higher (abstract) level to a lower (detailed) level, the screen space distance of any pair of geo-spatial points increases accordingly. Intuitively, the clusters at a higher level split into smaller ones at a lower level. Hence, the multi-scale nature of spatial clustering is consistent with a hierarchical representation that can be represented as a dendrogram (Figure 3).

We represent the multi-scale aggregates using a tree structure that naturally depicts the hierarchical relationships of the clusters at different scales. In this hierarchy, nodes represent individual spatial clusters, while the edges represent the parent-child relationships of clusters at adjacent spatial scales. The clusters that are formed at the same spatial scales correspond to the nodes that have the same depth in the tree.

Context-Preserving Visualization

In order to visualize the multi-scale hierarchy, TopoGroups creates a boundary-based visual representation using an implicit curve for each aggregate in the hierarchy (Figure 4(a)). The benefits of this particular representation lie in three aspects, referring to the six guidelines *G1* through *G6* by Elmqvist and Fekete [12]. First, the boundary within the context of a geographical space naturally depicts the spatial scope of the aggregate, which is intuitive and interpretable to the users (*G2, G6*). Second, while the data points are typically represented as small circles, the implicit curve is easily distinguishable from the data items (*G4*). Third, since the visual space inside the boundary of the higher level clusters can be utilized to visualize the lower level clusters, the boundary-based representation produces minimum visual clutter (*G3*).

We note that the overlapping of the boundaries at different scales may exist, as shown in Figure 4(b). To this end, we propose a bottom-up distortion algorithm (Figure 5) toward effective overlap minimization of the multi-scale spatial boundaries (*G3, G5*). This is inspired by the nested treemap design that adds padding to adjacent rectangles in order to highlight the parent nodes in the hierarchy more effectively [10]. Motivated by the force-directed drawing algorithm [15], our algorithm traverses the hierarchy from the bottom level and for each non-leaf node, the algorithm repositions the control points of the boundary that overlap with its children for the sake of both an aesthetic visual result and performance efficiency. The algorithm ensures an optimal amount of distance between adjacent boundaries to provide a visual budget for the boundary-based visual encodings and avoid visual clutter.

In order to facilitate effective visual perception of the hierarchical and statistical information of the geographical aggregates, TopoGroups provides a set of visual encoding strategies combining different perceptual dimensions including color, transparency, shading, and shapes. The strategies have been applied to the inner area of the aggregates as well as the boundary, which is inspired by Bristle Maps [20, 26] where map features (roads, subway line, city blocks, etc.) are associated with visual elements—bristles—in order to visually encode the multivariate information in the geographical region of interest. In TopoGroups, we aim to convey both univariate and multivariate attributes of the spatial aggregates through our visual encoding strategies. In the rest of this section, we illustrate our visual designs based on a practical usage scenario of multi-scale spatial aggregates generated from location-based social media data (Twitter) in Cleveland, OH during the 2016 Republican National Convention.

Univariate Attributes

Aggregates' univariate attributes typically include the volume of data points, size of the geographical area, scale of aggregation (zoom level), etc. This type of attributes can be encoded using either the color of the inner area of the cluster, or the width/color of the boundary. For example, the analyst is interested in investigating the scale of aggregation at which different clusters have formed in Cleveland during the RNC event, and learning the relationships of different clusters across scales. To this end, TopoGroups encodes the scale of the individual clusters by rendering the inner area using specific color schemes. Figure 6 illustrates the encoding strategy based on a blue-red color scheme where dark blue represents the abstract level while dark red represents the detailed level (T2, T3). Clusters of the same color indicate that they are generated at the same level. Different color schemes such as sequential or qualitative schemes can also be applied here. In order to evaluate whether color encoding can enhance the understanding of hierarchical relationships of multi-scale aggregates, and which color scheme achieves the best result, we conducted a user study (Details are discussed in the evaluation section).

In addition to filling the color, TopoGroups applies the halo effect on the boundary of the clusters (Figure 6(b)) in order to visually indicate the sidedness of the boundary [38]. The halo is only rendered at one side of the boundary (outer side of the cluster) in order to provide a visual cue in terms of which side of the boundary belongs to the cluster. The halo effect is especially helpful when the user zooms into a certain level where only the partial cluster is visualized in the viewport.

Multivariate Attributes

Aggregates' multivariate attributes are typically generated from classification or categorization of the data items, such as different topics extracted from social media message content. Assuming the analyst is curious about the major topics during

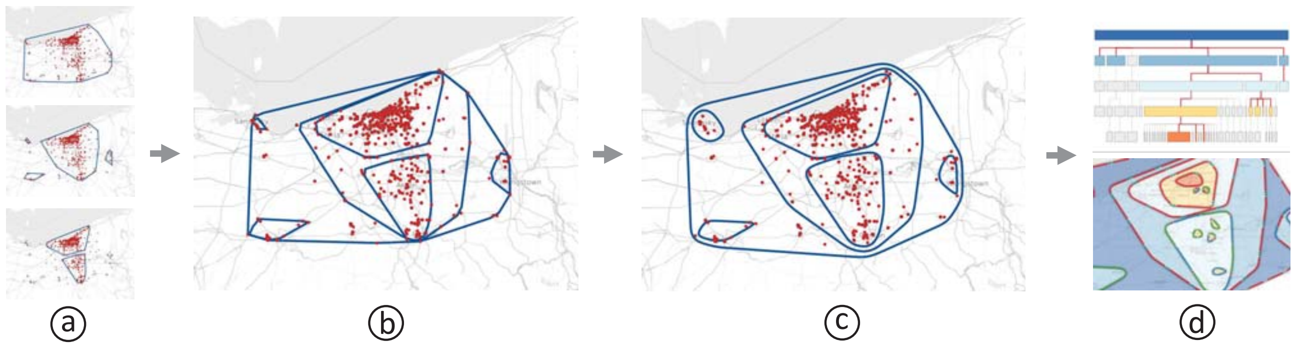


Figure 4. Spatial aggregates are generated (a) at multiple scales and coupled into one visual display using a boundary-based representation (b). The boundaries are properly distorted and smoothed to avoid visual clutter (c). Visual encodings and interactions are designed to facilitate effective exploration of multi-scale aggregates (d).

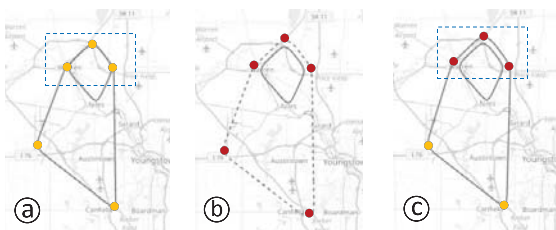


Figure 5. Boundary overlap minimization: (a) The boundaries of the parent and child overlap (highlighted in the dashed box); (b) The parent's boundary is inflated in order to avoid the overlap; (c) Part of the inflation result is used to form the new boundary of the parent.

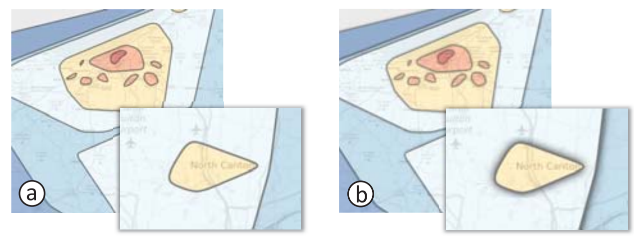


Figure 6. The area inside the multi-scale clusters is filled based on a blue-red color scheme from blue (abstract level) to red (detailed level) to indicate the aggregation level. The comparison of the visualization without halo (a) and with halo (b) is shown. With halo, it is easier for the user to determine which side of the boundary belongs to this cluster.

the RNC event, and wishes to further examine the prominent topics in different clusters at different scales, TopoGroups automatically extracts major topics (e.g., RNC-related, traffic and accident, drinking and entertainment) and provides several boundary-based encoding strategies to convey the quantitative information of different topics for the individual aggregates (T4) as Figure 7 shows. In all three designs, each color corresponds to a specific category:

- **Continuous colored segments**: Figure 7(a) shows line segments being used as the major visual element to convey the quantity of categories. The length of the colored segment is in proportion to the quantity of the corresponding category. Segments repeat to fill the entire boundary.
- **Discrete colored dashes**: Figure 7(b) shows a sequence of dashes being used to convey the quantity of categories. The number of colored dashes in each sequence is in proportion to the quantity of the corresponding category. Sequences repeat to fill the entire boundary. We choose the dash as the visual element in this design instead of circle or other similar shapes for the sake of visual discrimination between aggregates and data items (*G4*).
- **Stacked lines**: Figure 7(c) shows the entire boundary line of the cluster being used to convey the quantity of categories. The width of the boundary lines is in proportion to the quantity of the corresponding category. The lines for different categories are stacked next to each other.

We have conducted a user study to assess the efficacy of these techniques in conveying the categorical distribution, the details of which are discussed in the evaluation section. We also note that for both the continuous segments and discrete dashes, we fill the entire boundary of the clusters by concatenating the segments or dash sequences repetitively along the boundary. The rationale behind such a design is that the repetitive patterns avoid misleading the users in terms of interpreting the categorical information (Figure 8(b)). Without the repetitive patterns, the visualization can convey the wrong categorical information particularly when only a partial cluster is shown in the viewport (Figure 8(a)).

As Figure 1(left) shows, with the effective visual encodings provided in TopoGroups, the analyst clearly notices that while most of the tweets are related to RNC at an abstract scale (the major color in the outward cluster is red), as she investigates lower levels, the clusters within Cleveland are more related to RNC, while in the nearby cities more tweets relate to traffic (green) and drinking (blue). As she further zooms into the city of Cleveland, she identifies that drinking and traffic related tweets form several clusters around the suburban regions (Figure 1(right)). Therefore, TopoGroups provides a comprehensive picture in terms of how the different topics are correlated with the clusters at different spatial scales, and how they evolve from the overview level to the detailed level.

Interaction and Interface Design

TopoGroups consists of two visual and interactive dialogs: an interactive map view that visualizes the multi-scale aggregates within the same geographical display, and a tree view that

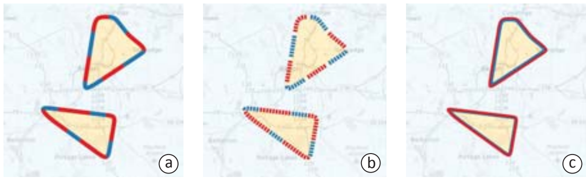


Figure 7. Design alternatives for encoding categorical information on the boundary: (a) Continuous colored segments; (b) Discrete colored dashes; (c) Stacked Lines.

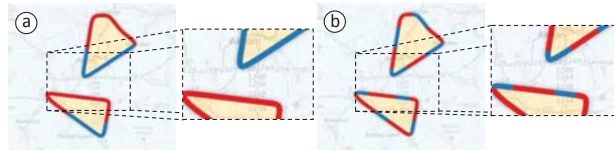


Figure 8. Without the repeating patterns (a), the visualization may convey the wrong categorical information when only the partial cluster is in the viewport. This visual confusion can be avoided by introducing the repeating patterns (b).

illustrates the hierarchical relationships of the multi-scale aggregates. These two dialogs are coordinated and seamlessly integrated when the users navigate across different scales.

General Navigation: The interactive map view allows the users to navigate across different spatial scales through common zooming operations (T2, T3). Each time the user zooms in or out, the map navigates to either the higher or lower adjacent level, respectively. TopoGroups visualizes the multi-scale spatial aggregates that are visible or partially visible in the map viewport. Aggregates that occupy too small screen space (i.e., less than 100 pixels) are not rendered (*G1*). TopoGroups also provides a configurable parameter S that restricts the number of adjacent scales to visualize (*G1*) in order to avoid computational performance issue and potential overload on the user. For example, if the user navigates to zoom level 10, with $S = 2$, then only the levels from 8 to 12 are visualized. After a visual inspection of the results, we found $S = 2$ to produce reasonable results with respect to performance and readability.

Muti-Scale Navigation through Selecting Targets: TopoGroups supports simple yet intuitive interactions that allow users to navigate across multiple levels. As the user double-clicks on a target aggregate, the map automatically pans to the target aggregate and zooms in to fit its extent (T3). With this design, the conventional navigation paradigm that requires multiple panning and zooming operations is simplified by a single and intuitive interaction that significantly alleviates the interaction overload. Furthermore, by double-clicking on the region outside the target aggregate, TopoGroups automatically resets the view back to the previous geographical space.

Exploring the Hierarchy — The Tree View: The tree view in TopoGroups illustrates the multi-scale hierarchy using both a dendrogram and a node-link diagram [41] (T1, T2). The dendrogram illustrates the scale of aggregation, as the nodes of the same scale are aligned based on the same vertical offset (Figure 4(d)). However, this may cause significant visual clutter when the number of nodes is large. Hence, TopoGroups provides a complementary node-link representation that fully utilizes the two dimensional space. The node-link diagram simply regards the hierarchical structure as a graph rendered using a force-directed layout. The user can toggle between the two views in the control panel.

The tree view is coordinated with the map view through the *brushing and linking* paradigm. As the user navigates on the map, the aggregates visible in the geographical space are highlighted in the tree view. With this design, while the user may focus on exploring the detailed levels on the map, the tree view provides a context of the entire structure to the user. When the user selects one or more nodes in the tree view, the corresponding aggregates on the map view highlight accordingly. The tree view supports filtering based on the domain-specific attributes of the aggregates such as geographical size, data volume and density. The user can also filter to show only a subtree by specifying a node as the root of that subtree. The view supports sorting the children (from left to right) of each tree node based on the aforementioned attributes.

Details-on-Demand: TopoGroups supports easy access to details-on-demand of the raw data items (T5). When the user right-clicks on the specific aggregate and selects the relevant option, the data items that belong to this aggregate are shown on the map as circles. Simultaneously, a separate message table shows the semantic content of those data items in a list and highlights the keywords relevant to different categories based on the same color scheme.

Implementation Details

TopoGroups consists of a multi-layered SVG canvas. The map layer stays at the bottom of the hierarchy and provides an interactive map visualization. On top of the map layer is the visualization layer, which is the primary workspace for rendering various visual elements including boundaries, halos, categorical encodings, etc. The toolbox layer stays on top of the hierarchy, showing interactive menus and the toolbar.

TopoGroups applies cardinal spline interpolation to smooth the boundary of the spatial aggregates. In order to fill color inside the boundary, the SVG `<mask>` command is used to create masks according to the boundary of the inner children aggregates, thus avoid rendering those areas. TopoGroups achieves the shadow (halo) effect by initiating an SVG filter (`<filter>`) and associates a Gaussian blur (`<feGaussianBlur>`) to the filter. The size of the shadow is controlled by the standard deviation (SD) of the Gaussian blur (`<stdDeviation>`). A higher SD value results in a larger shadow in screen space. The SD value in TopoGroups is set as 5, which achieves a satisfactory visual effect.

TopoGroups utilizes SVG dash styling to render colored line segments (each line segment is regarded as a long dash) and dash sequences along the boundary. Specifically, the `<stroke-dasharray>` attribute defines the patterns and gaps of the dash styling, and the `<stroke-dashoffset>` attribute controls the offset where the pattern begins. In order to visualize multiple categories, TopoGroups pre-calculates the dash patterns and offset for each category based on the categorical distribution, and then renders them iteratively.

EVALUATION

TopoGroups visualizes the hierarchical spatial aggregates and provides visual encoding strategies to indicate domain-specific attributes associated with individual aggregates. Our evaluation focuses on design alternatives for TopoGroups that convey hierarchical and categorical information, as we believe these low-level visual encodings are critical factors for multi-scale perception and context preservation. In order to focus on the task primitives, we break down the experiment into two aspects (Study 1: structural/hierarchical; Study 2: semantic/categorical) rather than introduce more complexity in the tasks, which may obfuscate the results.

Participants and Apparatus

We recruited 20 participants (age range of 19 to 28, 7 female, 13 male) for Study 1, and 20 participants (age range of 22 to 36, 6 female, 14 male) for Study 2. Most participants were students and staffs from our college of engineering, who have some basic understanding of the concepts being tested (e.g., spatial clustering, hierarchical structures). The participants were paid $5 for participation in one study. The experiments were conducted on a windows-based computer with a 30-inch Dell monitor. The interface for the main visualization occupied an area of 1600x1600 pixels.

Procedure

The two studies were conducted independently and had similar procedures. At the start of the study, the investigator asked the participants to sign a consent form and introduced the research background and the different visualization designs. Then the investigator provided a training session and presented sample questions covering major visual designs and task types to familiarize the participants with the tasks. In order to ensure that they did not have any difficulty or misunderstanding, the participants were provided with the correct answer and were asked to raise any questions or concerns to the investigator during the training. The accuracy and the completion time for each trial were recorded. After each study, the participants were asked to complete an online demographic survey.

User Study 1: Encoding the Hierarchical Information

This experiment evaluated the efficacy of color and different color schemes in terms of conveying the hierarchical structure of the spatial aggregates within the geographical space.

Techniques and Task Design

In this experiment, we utilized four different visual encoding strategies (visualization technique V) in the experiment:

- NoC Only the boundaries of the clusters are visualized. No color is rendered inside the cluster.
- SEQ A sequential color scheme is used to indicate the scale of aggregates. In TopoGroups blue is used as the main hue. Lighter colors represent higher scales (abstract level), and darker colors represent lower scales (detailed level).
- B-R A blue-red color scheme is used to indicate the scale of aggregates, which starts from blue (higher scales), transitions to yellow (middle scales), and ends at red (lower scales).
- QT A qualitative color scheme is used to indicate the scale.

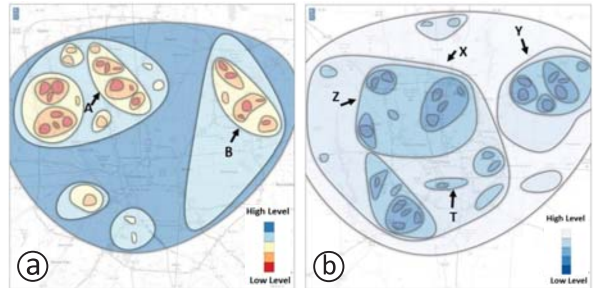


Figure 9. Task design in Study 1: (a) Comparing scales of aggregation (TSC); (b) Identifying parent-children relationships (TPC).

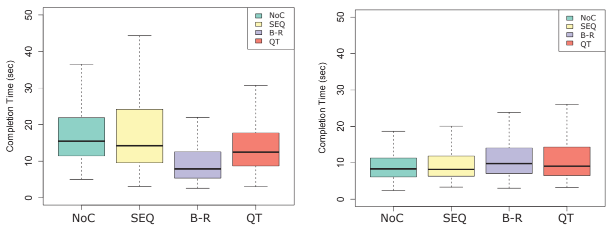
We developed two classes of typical tasks. The first class investigated the participants' performance in terms of visual comparison between scales of individual aggregates (TSC). A typical task of this class highlights two aggregates denoted as A and B, and the participants are asked to decide which one is at a higher (or lower) level (Figure 9(a)). The second class of tasks evaluated the participants' understanding in terms of parent-child relationships among aggregates at different scales (TPC). A typical task of this class specified a cluster denoted as T, and highlighted a set of clusters denoted as X, Y, Z. The participants were asked to decide which cluster among X, Y and Z contains T in the visualization (Figure 9(b)).

We controlled the difficulty level D of each trial based on the complexity of the cluster hierarchy. The hierarchy complexity is defined based on two parameters: the height (or depth) of the hierarchy (L), and the average number of children for each non-leaf node (C). Moreover, we define three difficulty levels: *easy* ($L \in \{3,4\}; C = 2$), *middle* ($L \in \{6,7\}; C = 4$), *hard* ($L \in \{9,10\}; C = 6$). Each trial consists of a multiple-choice question along with the visualization. The four techniques were presented in a counter-balanced order. The whole study consisted of 4 (technique) $\times$ 2 (task type) $\times$ 3 (complexity of hierarchy) $\times$ 2 (repetition) = 48 trials.

Results and Observations

The accuracy was quite high (average of 96.04%) across all visualization techniques for both tasks. Since there was no time limit for the tasks, the users were able to correctly identify the hierarchy of the spatial aggregates shown.

The completion time for the type 1 task (TSC) is shown in Figure 10(a). The results have been analyzed based on a repeated-measure analysis of variance (assumptions met). Visualization technique V had a significant main effect on completion time ($F(3, 57) = 27.12$, $p < .0001$). Pairwise comparison between visualization techniques using a Tukey HSD showed that all pairs have statistical significance ($p < .05$), except for the pair of no color (NoC) and sequential scheme (SEQ). As expected, the difficulty level D had a significant main effect on completion time as well ($F(2, 38) = 48.54$, $p < .0001$). Furthermore, there was a significant interaction effect between visualization technique V and difficulty level D on completion time ($F(6, 114) = 6.60$, $p < .0001$) As shown in Figure 10(a), the sequential scheme (SEQ) has the highest completion time (mean: 19.70 seconds), followed by no color (NoC) (mean: 18.14 seconds), then the qualitative scheme (QT) (mean: 14.49



(a) Completion Time (TSC) (b) Completion Time (TPC)

Figure 10. Completion time for the two types of tasks in Study 1. As the result indicates, color encoding the areas helps identify the scale of aggregation (a), but not the parent-child relationships (b).

seconds), and finally the blue-red scheme (B-R) (mean: 10.18 seconds). The blue-red color scheme had the lowest completion time, which can be explained by noting that this scheme consists of different hues diverging from the middle, making the encoding space a bit larger while retaining a step to step relationship between the shades at each level. The qualitative color scheme follows the blue-red scheme in completion time. This scheme facilitates the user tracing across multiple scales since equal levels are quickly identifiable by their color, and adjacent levels are also easily distinguishable. The sequential color scheme and no color scheme had the longest completion time. This can be explained by noting the sequential color scheme is based on a single hue, and requires a higher cognitive load for a user to identify the equal levels between very similar shades of the same color. Similarly, without rendering color in the aggregates, users have to identify the scales purely based on the nested boundaries, which adds to the cognitive overload. Based on the post-experiment survey, users seem to prefer the blue-red color scheme: one user commented: "I liked the contours with the blue-red color as it is the easiest to view and decreases my response time to answer."

The completion time for the type 2 task (TPC) is shown in Figure 10(b). Based on a repeated-measure analysis of variance, visualization type V had a significant main effect on completion time ($F(3, 57) = 2.87$, $p < .05$). However, for pairwise comparisons using a Tukey HSD, only no color (NoC) vs qualitative scheme (QT) and sequential scheme (SEQ) vs qualitative scheme (QT) were marginally significant ($p < .05$). The difference between the completion time for each technique (Figure 10(b)) was relatively small (QT: 11.92 seconds, B-R: 11.31 seconds, SEQ: 10.06 seconds and NoC: 10.04 seconds). This can be explained by the fact that although color changes across scale, there is little color diversity among different sub-groups of aggregates. As users are not able to intuitively identify these differences with the help of color, color may be of limited benefit in identifying the parent-child relationship.

Our guidelines for color encoding the multi-scale aggregates in order to convey hierarchical information are summarized in two aspects. First, color encoding the areas of multi-scale aggregates helps to identify the aggregation level. We found that a blue-red (or similar) color scheme is most effective toward this end. Second, while encoding the areas of multi-scale aggregates can assist identification of the aggregation level, it does not fully convey the parent-child relationships. Additional encoding or interaction designs are required, such as providing different sub-clusters with individualized color encoding or highlighting sub-clusters when a parent is selected.

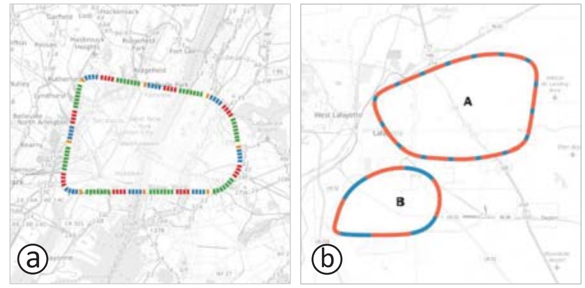


Figure 11. Task design in Study 2: Comparing categories within one aggregate (a) and across multiple aggregates (b).

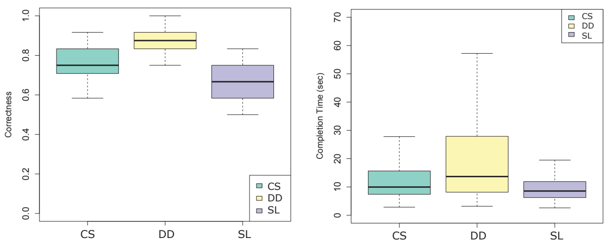
User Study 2: Encoding Categories on the Boundary

This section describes the experiment that evaluates the design alternatives in TopoGroups that encodes categorical information at individual aggregates.

Techniques and Task Design

In this experiment, we evaluated three design choices (visualization technique V) (Figure 7) for encoding categorical information on the boundary of the spatial aggregates: continuous colored segments (CS), discrete colored dashes (DD) and stacked lines (SL). Two types of tasks were involved in the experiment. For the first type of task, the participants were shown a single aggregate on the map, with the boundary being visualized according to an underlying categorical distribution (category set denoted as $S = \{C1, C2, C3...\}$). The participants were asked to identify the category that has the highest/lowest volume within category set S in the visualization (Figure 11(a)). For the second type of task, the participants were shown two aggregates denoted as A and B on the map, with the boundaries being visualized according to two different categorical distribution of the same category set: with one category denoted as $C1$ highlighted, the participants were asked to determine in which cluster (A or B) the category $C1$ is more prominent (has a higher proportion among all categories) (Figure 11(b)). For each type of task, the same visual design was applied to all the aggregates. The different categories were visualized based on a qualitative color scheme, appropriately adjusted so that when concatenating segments of different colors or stacking lines of different colors, the adjacent colors were easily distinguishable. Although the proposed designs are applied to multi-scale aggregates, the scale itself has a minimum effect on the visual perception of categories. Hence, we limit this study to a single scale to emphasize the impact of comparing categories within and across different aggregates.

We controlled the difficulty level D of each trial based on the size of the category set (2 and 4). Each trial consisted of a multiple-choice question along with the visualization. The three techniques were presented in a counter-balanced order. The whole study consisted of 3 (technique) $\times$ 2 (task type) $\times$ 2 (difficulty level) $\times$ 3 (repetition) = 36 trials.



(a) Accuracy (b) Completion Time

Figure 12. Accuracy and completion time for Study 2. Among the three design alternatives, the discrete dash design achieves the highest accuracy (a) and meanwhile requires the longest time (b).

Results and Observations

The results of accuracy (Figure 12(a)) show that the discrete dashes (DD) had the highest accuracy (average: 85.42%), followed by continuous segments (CS) (average: 76.67%) and stacked lines (SL) (average: 67.50%). The results have been analyzed based on the linear regression (glimmix) with the assumptions satisfied. Visualization technique V had a significant main effect on completion time ($F(2, 38) = 10.76$, $p < .0001$). Pairwise comparison between visualization techniques using a Tukey HSD showed that all pairs had statistical significance ($p < .05$). As expected, difficulty level D had a significant main effect on completion time ($F(1, 19) = 45.11$, $p < .0001$). The results reflect that calculating the number of dashes is more accurate than visually comparing the length of different segments, especially when the difference between the values is small. Furthermore, stacked lines was the least effective as the visualization budget (the entire width of lines) is too limited to visually reflect the variation of different values.

In terms of the completion time, the participants spent a relatively long time on the discrete dashes (DD) (20.46 seconds), followed by continuous segments (CS) (12.57 seconds) and stacked lines (SL) (9.00 seconds). Visualization technique V had a significant main effect on completion time ($F(2, 38) = 47.08$, $p < .0001$). Pairwise comparison between visualization techniques using a Tukey HSD showed that all pairs have statistical significance ($p < .05$). As expected, difficulty level D had a significant main effect on completion time as well ($F(1, 19) = 45.88$, $p < .0001$). The results indicate that although DD achieves the highest accuracy, it requires a longer time for the users to count the number of dashes in each category for comparison. In terms of visual perception, the number of visual units in this design is the largest, requiring a longer time for the users to perceive. When the length of the boundary is large, or the size of the dash is small, this can potentially result in a larger number of dashes and overload the users.

Our guidelines for encoding categories on the boundary are summarized in the following two aspects. First, the discrete dash design is the most effective in terms of the accuracy. This is useful in analyses where comparison accuracy is critical, and the quantitative difference between categories are potentially not obvious. Second, the continuous segment design should be used for analyses where speed is favored over accuracy, as the discrete dash design may overload users in extreme cases.

Experimental Results in Practice

Analyzing criminal, traffic and civil (CTC) incident data collected in the cities of West Lafayette and Lafayette, Indiana (more than 170000 incidents from 2010 to 2016) illustrates the use and benefit of the TopoGroups technique. Assume a police officer is interested in several crime types in these regions, including *liquor law violation*, *robbery* and *theft*, he starts the analysis by visualizing the multi-scale clusters at an overview level (Figure 13(left)). The user observes that while a huge cluster is formed at an abstract scale (county level) that covers the two cities, as the officer investigates lower scales (city level), the cluster splits into two smaller ones that are located around the downtown area of the two cities, indicating a high frequency of incidents. Furthermore, the two clusters are visually separated by the Wabash River, which is consistent with the fact that the river is a natural boundary between the two cities. With the continuous segment design applied to show the distribution of different crimes, the user also notices that while most of the incidents are related to *theft* at a higher scale (the major color in the outward cluster is green), the cluster within downtown West Lafayette is more related to *liquor law violation* (blue), while most incidents related to *theft* come from Lafayette and suburban areas in West Lafayette. Since Purdue University is located in downtown West Lafayette, this indicates the campus is safer than other regions (little *robbery* or *theft*), although many *liquor law violations* occur.

The user further zooms in to lower scales (street level) to examine the different patterns in the two cities. Figure 13(middle) shows the downtown West Lafayette where the campus is located. Interestingly, the user identifies several clusters around the campus malls and student activity centers where the *liquor law violation* is prominent. The mall on the east side of the campus also has a considerable number of *robbery* and *theft* incidents. The officer then navigates to Lafayette where the visual result indicates active *robbery* and *theft* activities around major shopping malls and supermarkets. Therefore with TopoGroups, while the user navigates across different scales or targets a specific scale, the visualization effectively preserves the context at other adjacent scales, thus reducing interaction and cognitive overload during the analysis process.

DISCUSSION

TopoGroups distorts the boundary of aggregates and couples multi-scale results in a single display in order to preserve the context of multiple scales. Our distortion method (Fig 5) has a minimal effect in terms of lowering the fidelity (*G5*) and interpretability (*G6*) of the boundary representation, since the proposed distortion approach enlarges the parent boundary that overlaps with its children. Hence, the data points that belong to a specific aggregate are guaranteed to stay within the boundary of the same aggregate after the distortion is applied. However, we note that the boundary itself is an approximate representation for aggregates, since the boundary merely depicts the spatial coverage of the corresponding data items instead of their accurate spatial distribution, and the distortion may further exaggerate the boundary and provide misleading results to the users. Compared to TopoGroups, conventional techniques (e.g., [14, 23, 42]) typically visualize a single-scale result in one visualization. Although they need interaction and

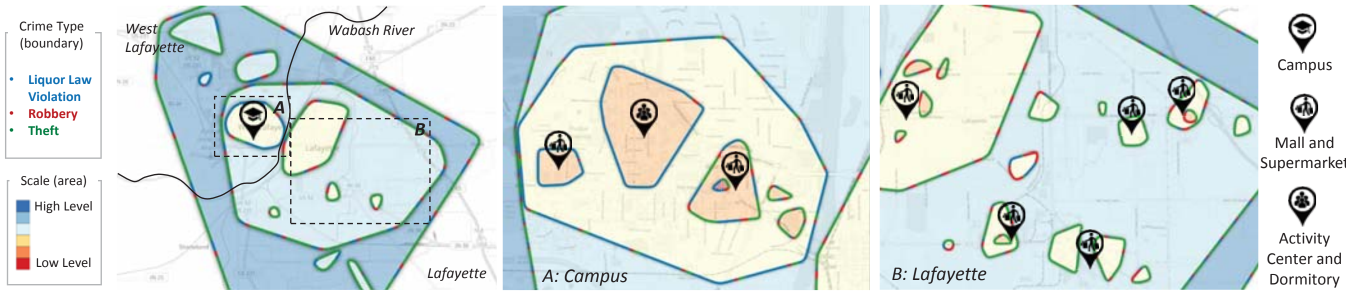


Figure 13. Multi-scale spatial aggregates of CTC incident data in West Lafayette and Lafayette, IN. Left: The campus has a high frequency of liquor violations while other regions show more incidents related to robbery and theft. Middle: Most incidents related to liquor violations occur around the campus malls and student activity centers. Right: Robbery and theft occur frequently around the shopping malls and supermarkets.

may create cognitive overload, these techniques present the original (accurate) analysis results that are intuitive for users to understand. Hence, conventional techniques are preferred in analysis tasks where geographical accuracy is required.

Although TopoGroups provides users with a configurable parameter *S* to restrict the number of adjacent scales visible from the current scale, further evaluations are required to explore the scalability of our approach. First, as the number of scales visible on the map increases, the amount of multi-scale information presented in the visual space increases accordingly, which can potentially burden or distract users especially when focusing on a specific level. Second, too many levels visible on the map may make it difficult for users to perceive the underlying map due to occlusion. Hence, TopoGroups is favored in analysis tasks that mainly require comparison or correlation of the analysis results across scales. In contrast, conventional techniques are more suitable for scenarios where users target several individual (discrete) scales of interest within the multi-scale analysis space.

Since TopoGroups summarizes the categorical information along the boundary within a geographical context, the users may associate the categorical information with the geographic information in the background. Unfortunately, the users may have the wrong interpretation that the visualization represents the local statistics near the boundary. We note that this is a limitation of this current design, and preventing this requires clear explanation or training to the users before they use the system. Future work could address this design limitation by encoding the locality of information into the boundary itself. For example, categorical data points could be projected to the nearest point on the cluster boundary, which would reduce potential errors over larger areas, and indicate the spatial distribution of the categorical information contained within.

Although TopoGroups visualizes multiple scales in the same display, the user may only focus on a specific scale (i.e., the current zoom level) while other scales are used to provide contextual information. A potential improvement might be to allocate more visualization budget (screen space) to the level on which one is focusing. This can be achieved by adding a weight parameter to the distortion algorithm so that boundaries of adjacent scales are shifted with larger offsets. This could provide an opportunity to encode more information within the chosen scale, perhaps layering different techniques on top of one another. For example, a semi-transparent sedimentation layer as a background would allow for users to quickly understand the categorical distribution while still being able to add other information relevant to the analysis space.

As a future extension, we would like to extend TopoGroups to visualize the semantic knowledge underlying the multi-scale aggregates. The prominent terms or phrases extracted from the content associated with the data items can be embedded within the aggregates, in order to maintain the semantic context across different scales. A potential issue associated with this text-based visualization is that some keywords that are of lower significance may have a longer length; thus, occupy more space and unduly draw the users' attention. A potential solution for this might be to dynamically adjust the font weight (thickness) in order to make the important words stand out.

CONCLUSION AND FUTURE WORK

Our primary contribution in this paper is a novel context-preserving visualization and navigation technique called TopoGroups for representing discrete spatial data as hierarchically clustered shapes. In terms of visual representation, we have explored the design space of different visual encodings for the boundaries and contents of each shape using color, transparency, and labels. In terms of interaction, we have described appropriate interactions for manipulating TopoGroups, including smoothly navigating in the cluster hierarchy. Results from a user study yielded guidelines on optimal visual encodings and interactions for the technique.

Spatially distributed data is ubiquitous, particularly in the domain of geolocated social media posts, so we see many potential future research directions in this area. Our future work includes integrating TopoGroups with text visualization, exploring the use of advanced text analytics techniques such as topic modeling, and applying the TopoGroups technique to full-fledged spatial visualization systems.

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