Hybrid Tree Visualizations for Analysis of Gerrymandering

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Abstract. In the United States, congressional redistricting follows a decennial Census. Gerrymandering can result from selection of district lines regardless of political parties. Understanding the relationships between the multiple dimensions in electoral data is a core goal of gerrymandering analysis. In this paper, we analyze patterns of gerrymandering in election data using a hybrid tree visualization technique that supports both overview and drill-down into a hierarchy of multidimensional relationships in that data. Visualization of hierarchical data is of major interest in information visualization. The technique utilizes a left-to-right node-link diagram to show overall hierarchical structure. Nodes in the diagram depict the levels in the dimensional hierarchy. Each node is rendered as an embedded view that shows its particular dimensional combination. Edges directly connect the contents of the embedded views to provide visual bridges that aid navigation and understanding of dimensional relationships. We demonstrate the utility of this hybrid technique is demonstrated through two use cases. This work aims to both ground and inspire the design of future visualizations for exploring gerrymandering.

Keywords: Tree visualization · Embedded views · Gerrymandering.

1 Introduction

The redrawing of electoral district lines following each decennial United States Census can significantly impact the outcome of elections that follow. Gerrymandering is a phenomenon in which district lines are drawn to favor a political party or certain groups. The electoral data of interest in gerrymandering analysis is a multidimensional mix of quantitative, categorical, temporal, and hierarchical geographic data types. Each state has multiple district cycles, and each district cycle involves multiple districts in that state. Gerrymandering analysis endeavors to understand such data by examining combinations of these dimensions including the various ways they may be meaningfully filtered, grouped, and aggregated. For this utility study, we mapped the data into a four-level hierarchy that progresses downward from election year to political party to redistricting cycle to district-level details. Exploring and analyzing these levels is critical to understanding the forms and effects of gerrymandering. Equipping gerrymandering analysts with the ability to drill down into different dimensional combinations of the data hierarchically is thus a key requirement for visual analysis tool design.

Visualization can help analysts to have insights, recall information, and communicate ideas about data. Hierarchical visualization techniques allow analysts to explore combinations of data dimensions by drilling down into those combinations visually. Multiple views facilitate identification of patterns within and comparison between such combinations. We integrate these two common approaches by embedding the views into the hierarchical visualization's nodes themselves. This approach offers a unified overview and drill-down for exploring different combinations of dimension. We enhance this integration by providing visual bridges that directly position and link the incoming edges from parent nodes and the outgoing edges to child nodes in relation to the corresponding visually encoded data in the embedded views. While we do not present usability results here, we hypothesize that this re-purposing of edges as a kind of visual linking [7] can improve interaction with and comprehension of the overall structure and the context of details in node-link styles of hierarchical visualizations. In this paper, we explore the potential of our integrated and enhanced technique for general application to multidimensional data through specific application to representative use cases in gerrymandering analysis. In particular, we demonstrate the technique's utility for analysis of key dimensional combinations in electoral data.

2 Related Work

This paper probes regions of the visualization design space that focus on mixed multidimensional data including hierarchical visualization and embedded views. The visualization design space has been extensively modeled and is increasingly populated. For sake of limited space we attempt only a cursory coverage here.

For general visualization design, Card and Mackinlay's framework offers guidance for the design of information visualizations with emphasis on the mapping between data and graphical context [5]. The visualization design space can be defined in terms of chart types and their combinations and enhancements [10, 9]. Guidelines for multiple view designs consider cognitive aspects including the effort required for comparison, context switching, user's working memory, and learning [33]. Gleicher, et al. consider designs for visual comparison [16] and propose a framework to design multiple views for comparison tasks [15]. It is important to consider both spatial and data relationships in composite visualizations [20]. More specifically for gerrymandering analysis, visualization of geospatial network information typically involves composition of geographic and network representations [25].

Diverse composite visualizations exist for hierarchical data. Tuples and attributes in tabular data can be divided to form an aggregation hierarchy, such as in *breakdown visualization* that supports drill-down from overview to details across hierarchies through small multiple views [8]. A node-link diagram juxtaposed with heatmap views visualizes sequences of transactions in information hierarchies [4]. A phylogenetic tree visualization superimposed in a map links with geographic locations through a linear geographic axis [24]. TreeVersity2 [17] presents a space-filling visualization called StemView that nests bars at each level of an icicle plot. VEHICLE [23] embeds hierarchical stacked bar charts into a node-link diagram for exploring conflict event data, and uses a radial tree layout with glyphs as nodes to visualize hierarchical information. DimLift [14] utilizes dimensional bundling and applies multiple composition and interaction techniques to facilitate the exploration of hierarchical data.

Hierarchical visualization techniques are organized primarily in terms the variety of ways to represent nodes and edges to capture structural relationships and data details [27]. Common techniques, such as node-link diagrams and treemaps [29], can be combined to create hybrid techniques such as *elastic hierarchies* [35]. The navigability and comprehensibility of node-link techniques can be improved through techniques such as hierarchical edge bundling to reduce visual clutter amongst edges [19]. Aggregation of edges can also be calculated in data space as a precursor to their representation in visual space [13]. The hybrid hierarchical visualization technique described in this paper utilizes both data and visual aggregation. Each level of the hierarchy involves dimension-specific data filtering, grouping, aggregation, and other statistics to calculate the data to show in each node/embedded view. Each embedded view effectively provides a visual aggregation over a set of node siblings. Visual bridging helps to convey the correspondence between the individually visualized edges and the corresponding features in the embedded views as visual aggregates.

3 Gerrymandering

Gerrymandering refers to the political manipulation of district boundaries to advantage a political party or group. Redrawing district lines can have intended or unintended consequences, such as letting politicians choose their voters, packing partisans, splitting communities, diluting minority votes, etc. [22]. When states redraw their districts, they may consider and balance various criteria. Common criteria such as equal population, minority representation, contiguity, compactness, communities of interest, etc. can be reviewed to ensure fair redistricting.

There are a variety of alternative measures of continuity and compactness for comparing the redistricting maps drawn by independent redistricting commissions to those by state legislatures [12]. In addition to measures based on redistricting criteria, the seats-votes relationship was highlighted for assessing the swing ratio and partisan bias of redistricting plans [32]. Moreover, the measure of electoral competition has contributed to comparison of redistricting plans. A recent study suggests that independent redistrictors may not increase electoral

Table 1. Precinct-Level data for the 2016 and 2020 elections in Oklahoma with congressional districts for the 2010 and 2020 redistricting cycles.

District 2010 Cycle	District 2020 Cycle	GEOID20	Party	Votes 2016	Votes 2020
2	2	40079000102	DEM	75	82
2	2	40079000102	REP	385	412
3	3	40113000113	DEM	17	14
3	3	40113000113	REP	37	40
3	3	40113000102	DEM	31	24
3	3	40113000102	REP	126	167

competition to achieve political neutrality [18]. Most recently, DeFord, Eubank, and Rodden [11] introduced a measure, *partisan dislocation*, to indicate cracking and packing by considering a voter's geographic nearest neighbors.

Rather than developing measures, researchers use automated redistricting algorithms to generate redistricting plans and perform a comparative analysis to reveal gerrymandering. Two types of redistricting algorithms that are commonly used in the redistricting literature are partitioning algorithms and swapping algorithms [21]. Besides these two types of approaches, a divide and conquer redistricting algorithm [21] integrates partitioning and swapping elements. Automated districting simulations that are blind to partisanship and race are used to measure the unintentional gerrymandering that can emerge from patterns of the geographic distribution of voters with regard to their partisanship [6].

Gerrymandering statistics can be difficult to interpret. Non-experts in particular may shy away from quantitative metrics that are hard to fully comprehend [31]. Our work is motivated by calls to make gerrymandering statistics more visually interpretable and less confusing for both experts and non-experts [22].

4 Data Model in Gerrymandering

In order to visually explore and analyze the precinct data as shown in Table 1, we utilize the features of our visual hierarchy design for gerrymandering analysis. It shows the votes for each party per precinct in the state of Oklahoma in the 2016 and 2020 elections. The data includes congressional districts for two redistricting cycles. For example, the 2010 cycle for the congressional districts in Oklahoma starts on May 10, 2011 and ends on Dec 31, 2021, whereas the 2020 cycle is from Nov 22, 2021 to Jun 30, 2031 [1]. We compare statistics between the two major parties. For example, the party with a higher voting share percentage (VSP) in a district, which is calculated by Equation (1) given $i \in precincts$ and $j \in parties$, wins the election for a House seat in the U.S. Congress.

$$VSP(votes|party = j) = \frac{\sum_i votes_i \wedge party = j}{\sum_i votes_i}. \tag{1}$$

Relationship $R(\{votes, party\})$ indicates the relationship between the votes variable and the party variable as shown in Equation (2). Here we use voting share percentage as the aggregate measure over precincts, and apply a relationship to it, such as $VSP(votes|party = Dem) > VSP(votes|party = Rep)$.

$$R(\{votes, party\}) : VSP(votes|party = a) > VSP(votes|party = b). \tag{2}$$

The relationship can be greater than ($>$) or smaller than ($<$), and we exclude the possibility of a tie ($=$) in a two-party contest.

In the gerrymandering analysis, the *state relationship* $R_{state}(\{votes, party\})$ indicates which party has a higher voting share percentage in the state level data, while a *district relationship* $R_{district}(\{votes, party\})$ is the relationship in the district-level. Congressional districts are divisions of a state. Seeing the relationship in each district could provide an important perspective on disparate results from elections. Given these relationships, a distance function can be applied to measure if two relationships $R_{state}(\{votes, party\})$ and $R_{district}(\{votes, party\})$ are the same or reversed:

$$d(R_{state}(\{votes, party\}), R_{district}(\{votes, party\})) = \begin{cases} 0 & \text{if same relationship} \\ 1 & \text{if reverse relationship} \end{cases} \tag{3}$$

For example, if $R_{state}(\{votes, party\})$ is the *state relationship* that Republicans have a higher voting share percentage and $R_{district}(\{votes, party\})$ is a *district relationship* that has lower voting share percentage for Republicans in a specific district, the distance between the two relationships is 1. Using a distance function alone can not reveal if a districting plan of a state is gerrymandered. One approach to assess gerrymandering is to examine all districts' distances. We propose a summary function S, defined in Equation 4, using relationship distance d and $|D|$ as the number of the unique distinct values in a redistricting plan. The value of S indicates what proportion of the districts do not follow the state relationship. If we compare the summary of district distances with the voting share percentage of the minority party at the state level, the disparity suggests that the districting plan is gerrymandered. For example, the minority party has a 40% voting share percentage at the state level, but the sum of the distances is 0.6 in a state with five districts. The sum indicates that the minority party should win the majority of the seats (3 out of 5). The different outcomes (i.e., 40% vs 60%) may be caused by gerrymandering.

$$S(votes, party, D) = \frac{1}{|D|} \sum_{\forall D_i \in D} d(R_{state}(\{votes, party\}), R_{D_i}(\{votes, party\})) \tag{4}$$

For the relationship, we apply the winning margin as shown in Equation 5 in the study of gerrymandering. The winning margin helps to examine the competitiveness of federal elections. By comparing the competitiveness of different redistricting plans, analysts can find additional support for the hypothesis that a redistricting plan is a partisan gerrymander.

$$VoteMargin = |VSP(votes|party = a) - VSP(votes|party = b)| \tag{5}$$

5 Visual Design

Our visualization technique is designed for visualizing relationships in hierarchical data structures that embed complex node information. To explore relationships, a node-link diagram is used to represent overall hierarchical structure.

The hierarchical structure is organized into a three-level tree structure as shown in Figure 1. The state relationship $R_{state}(\{votes, party\})$ maps to the node in the first level of the tree structure, and the $R_{district}(\{votes, party\})$ district relationships map to the nodes in the third level. The different *district cycles* are the nodes in the middle level of the tree, and they are connected to the state relationship and their own district relationships. To differentiate the relationship levels from the district cycle level in the node-link diagram, we use different shapes to encode their nodes. For example, circle nodes represent district cycles, and square nodes represent relationships in Figure 1. There are two reasons why we choose a node-link diagram over other hierarchical visualization techniques [28] like treemaps [29], Sunburst [30], or icicle plots [34] as a base representation. First, the non-leaf nodes for district cycle components are more expressive in a node-link diagram than in treemaps that strongly emphasize leaf nodes over all other nodes. Second, node-link diagrams have more flexible layouts than space-filling methods [26]. For example, it is easy to adjust the widths of each level in a node-link diagram to make room for embedded views.

We embed multiple views into nodes in our tree visualizations, and each view shows a different dimensional combination that relates to the nodes. The visualizations provide the visual bridging that analysts can follow from the view of the parents to the view of the children. The visual bridging also indicates the relationship between the nodes in the host tree visualization and the visual objects in the embedded view.

Color is a powerful visual channel to guide attention. We try to pick better color schemes for different components in our hybrid visualization system. First, we consider the well-known colors in our application domain which is political science. The color blue is associated with the Democratic Party, and the red represents the Republican Party. The political colors are reserved for the embedded charts that convey political parties' information. Next, we select a yellow-green sequential color palette to encode the *distance* and summary distance values in both tree nodes and relevant elements in the embedded view. The color green and yellow are visually distinguishable from the predefined political colors. The yellow-green sequential color palette is more easily distinguishable between low

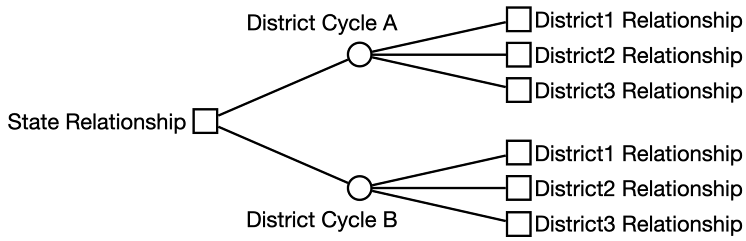

Fig. 1. The hierarchical view design for the gerrymandering analysis.

distance values and high distance values than the green only sequential color palette, especially when the distances in the leaf nodes are either 0 or 1. Last but not least, we exclude the predefined colors above and use other colors based on different hue channels for the charts in the hybrid visualization.

6 Analysis Examples

In this section, we describe how the visualization technique can be applied to the electoral precinct data of the U.S. presidency from *Dave's Redistricting App* [2] and congressional redistricting data from *All About Redistricting* [1]. For our analysis, we applied the 2016 and 2020 presidential vote share data at the precinct level. The election data was disaggregated to 2020 census blocks following the method described by Amos, et al. [3].

6.1 Evaluating the Efficiency Gap

This use case was inspired by an evaluation of the efficiency gap [31]. The relationship between seats and votes in the two-party system [32] could indicate the efficiency gap. We inspect changes of the efficiency gap before and after the redistricting plan. We start by looking at the structure of the hierarchical data. Our tree visualization has four levels, as shown in Figure 2(a). Looking at the heatmap view of the root node, we observe that there are two relationships in the electoral data set. The first relationship is *R({Votes2016, Party})*, representing the relationship extracted from the precinct-level votes data of the 2016 presidential election and each party's information. The second relationship *R({Votes2020, Party})* applies to the 2020 presidential election. In the first level of the tree, the two relationships are split into corresponding branches. The next level shows the district cycles, in which we see that the congressional districts for each election year are split into 2010 and 2020 cycles. By comparing these two cycles, we can gain insight into how the new redistricting plan has an impact on the election. The last level shows the leaf nodes that present the congressional districts for each combination of a district cycle and an election year.

We further investigate the details in each tree level as shown in Figure 2(b). In the first level, the mean distance aggregated for the relationship *R({Votes2020,*

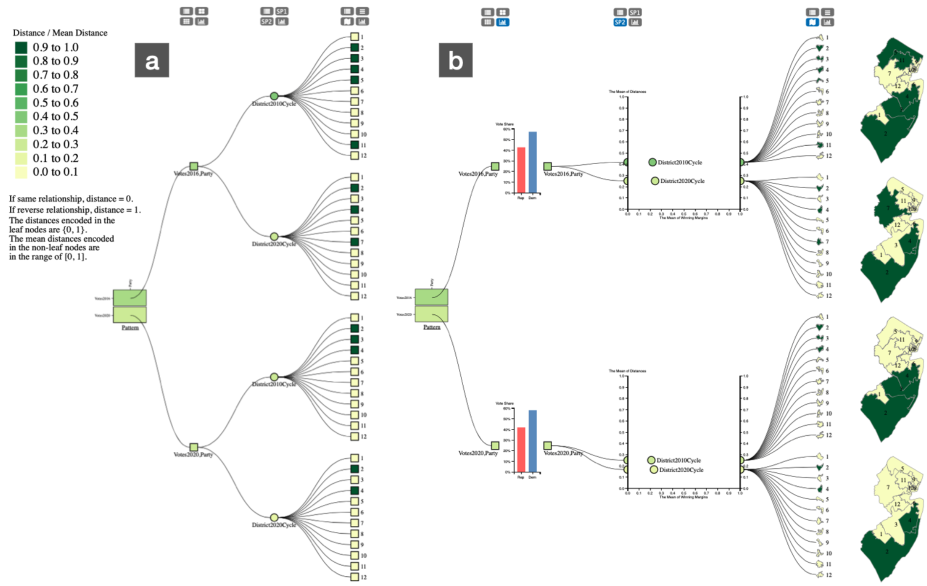

Fig. 2. An example demonstrating the design of the visualization for evaluating the efficiency gap. (Note that here we root the tree one level higher to add a summary of the state relationships.) The user first visualizes an initial tree visualization (a). Later, the user selects three views to embed into the tree visualization (b): a bar chart comparing vote shares between two parties, a scatterplot showing summary statistics, and a map view providing more context for districts in New Jersey.

$Party\})$ is 0.208. By clicking the show view button for views in the first level, we see that the state relationship $R_{state}(\{Votes2020, Party\})$ is that Democrats receive a higher vote share than Republicans in the presidential election (58% vs 42%). At the district cycle level, a scatterplot shows the statistics calculated for the two districting cycles. We find that the mean distance in the 2020 district cycle is 0.167. Comparing this number to the vote share for Republicans, it is obvious that the discrepancy between overall statewide support (42%) for Republicans and the proportion of their winning districts (16.7%) indicates partisan bias and hence supports a contention of gerrymandering. In addition, we see that the 2020 district cycle has a lower mean distance than the 2010 district cycle. This shows that partisan bias is higher under the new districting plan.

To understand the disparity and examine the congressional district lines, we inspect individual districts in the leaf nodes. We observe that the distances for District 2, 3, and 4 in the 2010 cycle are equal to 1, which represents a reverse district relationship compared to the state relationship. In contrast, the districts whose distance is 1 in the 2020 district cycle are District 2 and District 4. Since District 3 is no longer showing the reverse relationship, we investigate several aspects of gerrymandering. One crucial aspect relating to gerrymandering is whether the congressional district lines of the flipping district are drawn differ-

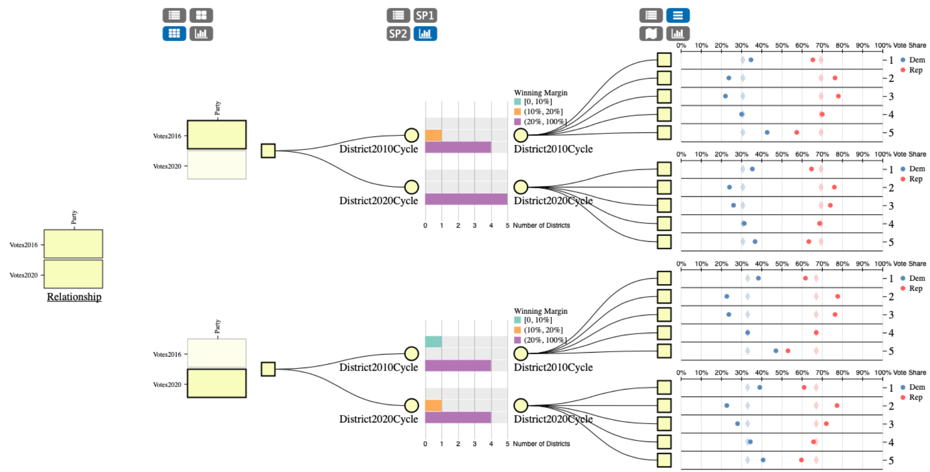

Fig. 3. Example of the hybrid tree visualization to assess electoral competition. (Note that here we root the tree one level higher to add a summary of the state relationships.) The user selects a heatmap view in the first level, a grouped bar chart in the district cycle level to explore changes in competitiveness between the two districting cycles, and a strip plot in the leaf level to show vote details for districts in Oklahoma.

ently in the new districting plan. The embedded map view clearly shows that the congressional district lines for District 3 are quite different between the two district cycles. Another aspect is to check the degree of partisanship. Switching to a strip plot at the leaf level, we find that the vote shares for the two parties in District 3 are extremely close in the 2010 cycle (50.1% Republican versus 49.9% for Democrat), while the vote shares in the 2020 cycle are much further apart (58.1% Democrat versus 41.9% Republican). Meanwhile, the vote shares for the Democratic party in the adjoining districts including Districts 2 and 4, decreased in the 2020 cycle, whereas the vote shares for the Republican party increased. This indicates possible gerrymandering tactics like cracking and packing. In this case, the Republican voters may have been cracked from District 3 into District 2 and 4; consequently, those votes are diluted. Concomitantly, the Democratic voters from District 2 and 4 might have been packed into District 3.

Through this exploration, we gained an understanding of how district lines are drawn and what consequences may affect future elections. This use case validates the effectiveness of the visualization to identify potential gerrymandering, and suggests further exploration. Our visualization supports smooth navigation and drill-down into each level of the hierarchy. The features of the visualization thus facilitate visual identification and comparison for gerrymandering analysis.

6.2 Assessing Electoral Competition

In the second use case, we demonstrate how we utilize our visualization to investigate the redistricting plan that appears to impact electoral competition.

Figure 3 shows the hybrid tree visualization for the presidential election in Oklahoma. In this case, the root level and the first level are not connected by lines; instead, the two duplicated and highlighted views in the first level implicitly represent the parent-child relationships with the root node. The mean distances of the internal nodes and the distances of the leaf nodes are all 0, as indicated by their respective fill colors. This clearly indicates that the district relationships are compatible with the state relationship in which the Republican party always wins every district in Oklahoma.

Since we are particularly interested in the recent election, we track the lower branch which presents the relationship *R({Votes2020, Party})*. When we look at the bar chart at the district cycle level, we find that one highly competitive district (i.e., a winning margin of 0% to 10%) in the 2010 cycle becomes less competitive in the 2020 cycle; the number of moderately competitive districts (i.e., a winning margin of 10% to 20%) changes from 0 to 1 after redistricting.

To delve more deeply into these changes, we more closely examine individual districts' voting shares. We embed a strip plot in the leaf level, and examine the changes of the voting shares for the two parties. We find that the competition is close in District 5 in the 2010 cycle (i.e., Republican 52.9% vs. Democrat 47.1%), and that the difference between the shares of the votes for the two parties becomes larger in the 2020 cycle (i.e., 59.5% Republican vs. 40.5% Democrat). This indicates that District 5 is probably safer and more secure for Republicans after redistricting. In addition, we find that District 3, which is a neighbor of District 5, shrinks its winning margin in the 2020 district cycle. We assume that the district lines for both districts were redrawn in the new redistricting plan. To confirm this, we switch to map views in the leaf nodes and observe a notable difference in the border between the two districts.

Our findings in Oklahoma are a strong sign that gerrymandering can occur even without overturning elections. We conclude that Districts 3 and 5 were likely gerrymandered to protect Republican candidates, especially in District 5. The embedded views show different facets of data for their respective purposes, and visual bridging enables an understanding of the relationships between them. More generally, flexible view choice allows for alternative designs that scale to accommodate two or more parties and few or many districts, such as by adding visual links from district nodes to map regions in Figure 2(b). Overall, our hybrid tree visualization technique aids in exploring hierarchical structure in gerrymandering and gaining a deeper understanding of the underlying information.

7 Conclusion

In this paper we introduce a hybrid tree visualization technique to explore hierarchical structure in the gerrymandering domain. Through two use cases, we demonstrate that the technique allows users to gain insights about gerrymandering of congressional districts. The use cases indicate that the hybrid visualizations enhance not only the exploration of the hierarchical structure but also the understanding of the complex relationships within and between the underlying data dimensions. We plan to continue this work on utility assessment presented here with usability studies of the two visualizations and others in realistic application by expert and casual analysts in the gerrymandering domain.

References

1. All About Redistricting. https://redistricting.lls.edu
2. Dave's Redistricting App. https://davesredistricting.org
3. Amos, B., McDonald, M.P., Watkins, R.: When boundaries collide: Constructing a national database of demographic and voting statistics. Public Opinion Quarterly **81**(S1), 385–400 (2017)
4. Burch, M., Beck, F., Diehl, S.: Timeline trees: visualizing sequences of transactions in information hierarchies. In: Proceedings of the Working Conference on Advanced Visual Interfaces. pp. 75–82 (2008)
5. Card, S.K., Mackinlay, J.: The structure of the information visualization design space. In: Proceedings of VIZ'97: Visualization Conference, Information Visualization Symposium and Parallel Rendering Symposium. pp. 92–99. IEEE (1997)
6. Chen, J., Rodden, J.: Unintentional gerrymandering: Political geography and electoral bias in legislatures. Quarterly Journal of Political Science **8**(3), 239–269 (2013)
7. Collins, C., Carpendale, S.: Vislink: Revealing relationships amongst visualizations. IEEE Transactions on Visualization and Computer Graphics **13**(6), 1192–1199 (2007)
8. Conklin, N., Prabhakar, S., North, C.: Multiple foci drill-down through tuple and attribute aggregation polyarchies in tabular data. In: Proceedings of the IEEE Symposium on Information Visualization. pp. 131–134. IEEE (2002)
9. Crisan, A., Fisher, S.E., Gardy, J.L., Munzner, T.: GEViTRec: Data reconnaissance through recommendation using a domain-specific visualization prevalence design space. IEEE Transactions on Visualization and Computer Graphics **28**(12), 4855–4872 (2021)
10. Crisan, A., Gardy, J.L., Munzner, T.: A systematic method for surveying data visualizations and a resulting genomic epidemiology visualization typology: GEViT. Bioinformatics **35**(10), 1668–1676 (2019)
11. DeFord, D.R., Eubank, N., Rodden, J.: Partisan dislocation: A precinct-level measure of representation and gerrymandering. Political Analysis pp. 1–23 (2021)
12. Edwards, B., Crespin, M., Williamson, R.D., Palmer, M.: Institutional control of redistricting and the geography of representation. The Journal of Politics **79**(2), 722–726 (2017)
13. Elmqvist, N., Fekete, J.D.: Hierarchical aggregation for information visualization: Overview, techniques, and design guidelines. IEEE Transactions on Visualization and Computer Graphics **16**(3), 439–454 (2009)
14. Garrison, L., Müller, J., Schreiber, S., Oeltze-Jafra, S., Hauser, H., Bruckner, S.: DimLift: Interactive hierarchical data exploration through dimensional bundling. IEEE Transactions on Visualization and Computer Graphics **27**(6), 2908–2922 (2021)
15. Gleicher, M.: Considerations for visualizing comparison. IEEE Transactions on Visualization and Computer Graphics **24**(1), 413–423 (2017)
16. Gleicher, M., Albers, D., Walker, R., Jusufi, I., Hansen, C.D., Roberts, J.C.: Visual comparison for information visualization. Information Visualization **10**(4), 289–309 (2011)

17. Guerra-Gomez, J., Pack, M.L., Plaisant, C., Shneiderman, B.: Visualizing change over time using dynamic hierarchies: TreeVersity2 and the StemView. IEEE Transactions on Visualization and Computer Graphics **19**(12), 2566–2575 (2013)
18. Henderson, J.A., Hamel, B.T., Goldzimer, A.M.: Gerrymandering incumbency: does nonpartisan redistricting increase electoral competition? The Journal of Politics **80**(3), 1011–1016 (2018)
19. Holten, D.: Hierarchical edge bundles: Visualization of adjacency relations in hierarchical data. IEEE Transactions on Visualization and Computer Graphics **12**(5), 741–748 (2006)
20. Javed, W., Elmqvist, N.: Exploring the design space of composite visualization. In: Proceedings of the 2012 IEEE Pacific Visualization Symposium. pp. 1–8. IEEE, Songdo, South Korea (2012)
21. Levin, H.A., Friedler, S.A.: Automated congressional redistricting. Journal of Experimental Algorithmics (JEA) **24**, 1–24 (2019)
22. Levitt, J.: A citizen's guide to redistricting. Available at SSRN 1647221 (2008)
23. Mayer, B., Lawonn, K., Donnay, K., Preim, B., Meuschke, M.: VEHICLE: Validation and exploration of the hierarchical integration of conflict event data. Computer Graphics Forum **40**(3), 1–12 (2021)
24. Parks, D.H., Beiko, R.G.: Quantitative visualizations of hierarchically organized data in a geographic context. In: 2009 17th International Conference on Geoinformatics. pp. 1–6. IEEE (2009)
25. Schöttler, S., Yang, Y., Pfister, H., Bach, B.: Visualizing and interacting with geospatial networks: A survey and design space. Computer Graphics Forum **40**(6), 5–33 (2021)
26. Schulz, H.J., Schumann, H.: Visualizing graphs-a generalized view. In: Tenth International Conference on Information Visualisation. pp. 166–173. IEEE (2006)
27. Schulz, H.J.: Treevis. net: A tree visualization reference. IEEE Computer Graphics and Applications **31**(6), 11–15 (2011)
28. Schulz, H.J., Hadlak, S., Schumann, H.: The design space of implicit hierarchy visualization: A survey. IEEE Transactions on Visualization and Computer Graphics **17**(4), 393–411 (2010)
29. Shneiderman, B.: Tree visualization with tree-maps: 2-d space-filling approach. ACM Transactions on Graphics (TOG) **11**(1), 92–99 (1992)
30. Stasko, J., Zhang, E.: Focus+ context display and navigation techniques for enhancing radial, space-filling hierarchy visualizations. In: Proceedings of the IEEE Symposium on Information Visualization 2000. pp. 57–65. IEEE (2000)
31. Stephanopoulos, N.O., McGhee, E.M.: Partisan gerrymandering and the efficiency gap. The University of Chicago Law Review **82**, 831 (2015)
32. Tufte, E.R.: The relationship between seats and votes in two-party systems. American Political Science Review **67**(2), 540–554 (1973)
33. Wang Baldonado, M.Q., Woodruff, A., Kuchinsky, A.: Guidelines for using multiple views in information visualization. In: Proceedings of the Working Conference on Advanced Visual Interfaces. pp. 110–119. Palermo, Italy (2000)
34. Woodburn, L., Yang, Y., Marriott, K.: Interactive visualisation of hierarchical quantitative data: an evaluation. In: 2019 IEEE Visualization Conference (VIS). pp. 96–100. IEEE (2019)
35. Zhao, S., McGuffin, M.J., Chignell, M.H.: Elastic hierarchies: Combining treemaps and node-link diagrams. In: Proceedings of the IEEE Symposium on Information Visualization, 2005. INFOVIS 2005. pp. 57–64. IEEE (2005)