Interactive Web Mapping for Multi-Criteria Assessment of Redistricting Plans

Jacob Kruse[a], Song Gao[a*], Yuhan Ji[a], Kenneth Mayer[b]

[a] Geospatial Data Science Lab, Department of Geography, University of Wisconsin-Madison, Madison, USA
[b] Department of Political Science, University of Wisconsin-Madison, Madison, USA
* Corresponding Author: song.gao@wisc.edu

Keywords: redistricting, gerrymandering, mobility, geovisualization

Introduction

Redistricting is the process by which electoral district boundaries are drawn. Though most redistricting rules in the United States were written before the invention of computers, maps are now made and contested with the aid of computers (MacDonald et al., 2005; Turner et al., 1999) and state of the art regionalization algorithms (DeFord et al., 2019; Aydin et al., 2018; Guo, 2008; Duque et al., 2007). Meanwhile, results from the past several decades of computational redistricting research also has researchers asking "what is the point of redistricting and how do redistricting criteria aid that?" (Nagle, 2019; Cain et al., 2018; Webster, 2013). While we do not attempt to definitively answer those questions here, we do attempt to shed some light on both. In particular, we describe 1) the use of the ReCom regionalization algorithm (DeFord et al., 2019) to explore values for a novel redistricting criterion, the modularity ratio, that helps capture the mobility flows of communities underlying districts in a quantitative way, and 2) an interactive web map designed to help educators, policy makers, and researchers understand how various redistricting criteria are in tension with each other.

Methods

We first describe different redistricting criteria and a regionalization algorithm (ReCom), and then go on to detail the interactive web map for demonstrating the resulting maps and exploring different redistricting criteria.

Redistricting Plan Generation and Evaluation Criteria

Generally, a community is a group defined by more similarity between its members than with members of a different group, and this is captured in four ways by redistricting law in the US. Most obviously, the Voting Rights Act mandates majority-minority districts to protect the voting power of minority demographic group (Pierre-Louis, 1995). Similarly, several states, consider communities of interest when drawing legislative districts (Mac Donald, 2013; Makse, 2012; Morrill, 1987). A number of states also require that political subdivisions, such as municipalities, not be split unless necessary (Winburn, 2008). More subtlety, requirements for contiguity and compactness rely upon our intuition that people tend to have more in common with people that live nearby (Webster, 2013; Altman, 1998). However, none of these definitions can be used to measure the degree to which communities are kept intact across all districts.

In the community detection literature, modularity is a common metric for describing the strength of communities, with maximization of modularity being one of the primary goals (Chen et al., 2014). In the context of redistricting, we wish to detect groups of people that have more connections with each other than they do with people from different regions, which we measure here with mobility flows. To measure the flow of people from one area to another, we employ SafeGraph mobility flow data, which measures the number of mobile devices that move from one census block group to another during a given time span. We then scale these counts to the population using the number of devices in each region and census data (Kang et al. 2020).

Using the scaled mobility flow data, we then calculate modularity as the sum of district intra flows divided by the sum of district inter flows, which is demonstrated in the example districts in Figure 1 and the following equation. Given how modularity is calculated here, we refer to it as the *modularity ratio* for clarity.

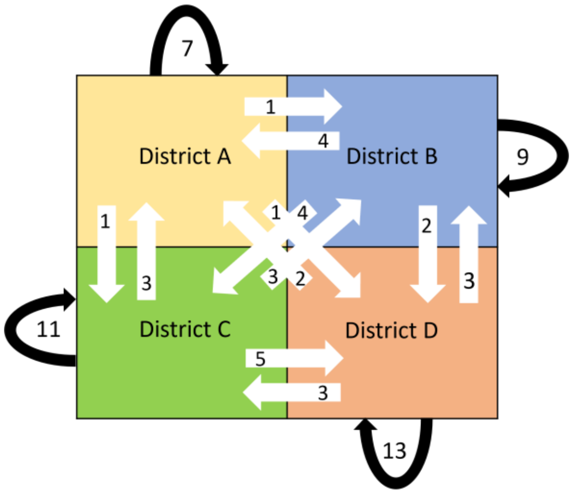

Figure 1: An example set of districts and flows.

$$Modularity\ Ratio = \frac{Sum\ of\ Intra\ Flows}{Sum\ of\ Inter\ Flows}$$

$$= \frac{7_{AA} + 9_{BB} + 11_{CC} + 13_{DD}}{1_{AB} + 1_{AC} + 1_{AD} + 4_{BA} + 4_{BC} + 2_{BD} + 3_{CA} + 3_{CB} + 5_{CD} + 2_{DA} + 3_{DB} + 3_{DC}}$$

$$= \frac{40}{32} = 1.25$$

Rather than trying to optimize the modularity ratio, we instead focus on exploring how districts would look if communities are captured by districts to varying degrees. To do so, we employ the recombination (ReCom) algorithm developed by DeFord et al. (2019) to build a representative sample distribution of valid district maps. We choose this algorithm because of the novel approach to Markov Chain Monte Carlo (MCMC) sampling using recombination, which allows the algorithm move much more efficiently across the state space, while also providing the benefits of sampling from a distribution of district maps that are acceptably compact, as well as meeting contiguity and equal-population requirements. The algorithm works in the following way:

1. Construct dual graph $G = (V, E)$, where each vertex from V represents a geographic unit, and adjacent vertices are connected by an edge from E
2. Initialize a partition P on G , which is the initial district assignments for all vertices in G
3. Specify the number of districts to merge (l) for each iteration, specify how many $iterations$ to run the algorithm for, and the permitted population deviation between districts
4. While $iteration\ count\ <\ iterations$:
    - Select l adjacent districts from P
    - Form an induced subgraph H with the selected nodes
    - Create a new partition that produces l districts that are within the permitted population deviation

To demonstrate how the modularity ratio varies with other common redistricting considerations, we also calculate compactness and the efficiency gap for the districts produced by the ReCom algorithm. For compactness, we use the Polsby-Popper measure (Polsby and Popper, 1991) which is defined as the following:

$$Polsby - Popper\ Compactness\ =\ \frac{4\pi Area}{Perimeter^2}$$

The efficiency gap is a measure of election fairness which combines wasted votes for both parties into one number (Stephanopoulos et al., 2015). As is common practice, we calculate the efficiency gap using only votes cast for the two major parties. As such, the efficiency gap is calculated using votes from all districts with the following formula:

$$Efficiency\ Gap = \frac{Democratic\ Wasted\ Votes - Republican\ Wasted\ Votes}{Total\ Votes}$$

The ReCom algorithm implementation and calculations for Polsby-Pooper and the efficiency gap are performed with the GerryChain python package (Metric Geometry and Gerrymandering Group, 2022).

Interactive Web Map Development

Experts from a wide range of disciplines, including education, policy, and academic research, have an interest in redistricting. To allow experts from such fields to explore the plans generated in this work, we provide an interactive web map. Using the results from the ReCom algorithm, we calculate the maximum values found by the algorithm for the modularity ratio, the efficiency gap, and compactness, respectively, and present them in the web map, along with demographic attributes. To encourage exploration as a learning method for the user, we present two side-by-side interactive maps, as well as linked, scented widget, which cues users into the attribute values underlying districts. Further down the page, we also provide linked text descriptions for each of the calculated metrics.

The web map itself is developed using a technology stack including JavaScript, HTML, and CSS, Leaflet, D3, and Map Sync libraries to provide the interactive mapping components.

Results

Multi-Criteria Assessment

Running the ReCom algorithm for 1000 iterations produced a wide range of values for the three criteria calculated. The efficiency gap ranged in value from –0.34 to 0.17, where the values are the fraction wasted votes across each of the maps produced. The compactness scores ranged from 0.12 to 0.28. Finally, modularity values ranged from 0.59 to 1.71. To understand how these criteria vary together, we present Figure 2, which plots the calculated metrics in 3-dimensional space, where each point represents on districting plan produced by the ReCom algorithm.

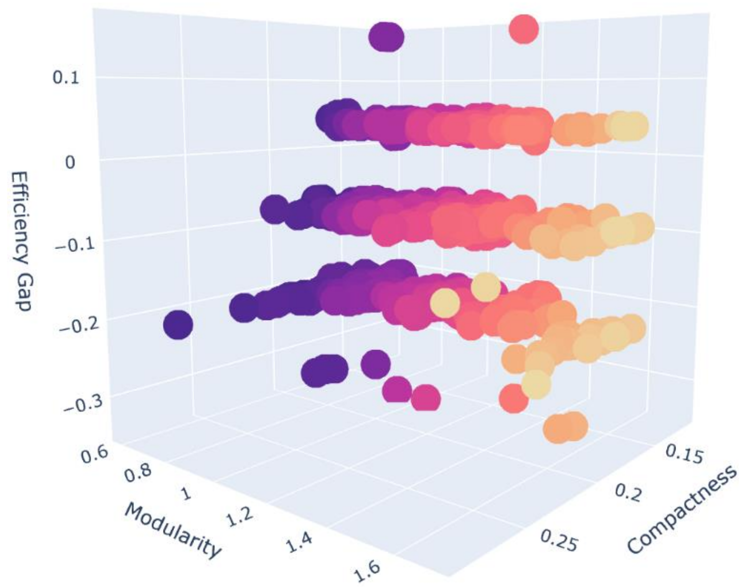

Figure 2. Multi-criteria cube of ReCom algorithm results.

Interactive Web Map

In the web map (Figure 2), users are allowed to choose from Wisconsin congressional district plans that optimize for the modularity ratio, compactness, and the efficiency gap, respectively, while also providing the currently enacted district map and a map from the People's Map Commission, for reference. Demographic attributes and flow values for each district can be visualized on the choropleth maps by selecting the corresponding header on the parallel coordinate plot. The same values can also be resymbolized as bar plots or proportional symbol maps. Finally, an Open Street Map base map provides context by showing city and road names.

The two map panels are synchronized, such that the panning or zooming on one map is performed in equal measure on the other map. Map interaction, synchronization and the ability to select which variable to display are key features in making this web map educational. Through playing with the map and trying out different interactions, users can get a better grasp of how map attributes relate to each other.

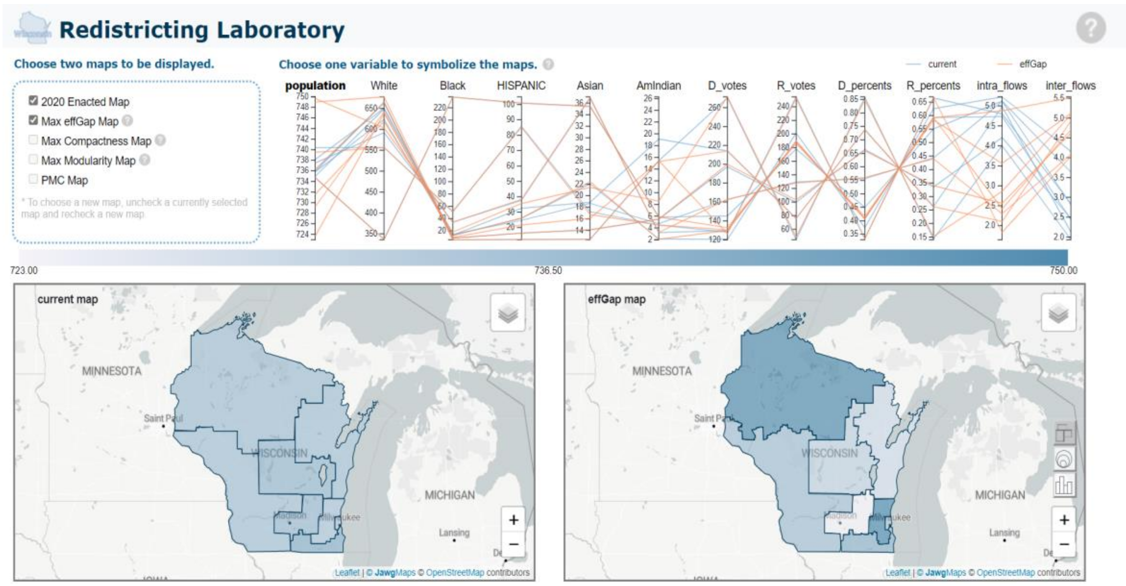

Figure 2: The user interface of the interactive web map for redistricting.

Discussion and Conclusion

Currently, much redistricting research is focused on understanding how a given district map compares to other valid maps. In this work, we provide a tool that allows users compare maps through interaction, providing an educational tool for redistricting researchers. With regards to how redistricting is performed and evaluated, we demonstrate how real communities can be measured and incorporated into map selection with human mobility flow data.

Future Work

Since this work is still in progress, we plan to add several features before making this work available to the public. Firstly, we plan to add district-level compactness and efficiency gap scores as attributes that can be visualized in the web portal. Secondly, we plan to include other visualizations to show the wide range in district plans with regards to the modularity ratio, the efficiency gap, and compactness. While we have preliminary results, we plan to run further experiments to find the widest possible variety of modularity scores.

Acknowledgements

The work is supported by the University of Wisconsin 2020 WARF Discovery Initiative funded project: Multidisciplinary approach for redistricting knowledge.

References

Altman, M. (1998). Modeling the effect of mandatory district compactness on partisan gerrymanders. Political Geography, 17(8), 989-1012.

Altman, M., MacDonald, K., & McDonald, M. (2005). From crayons to computers: The evolution of computer use in redistricting. Social Science Computer Review, 23(3), 334-346.

Aydin, O., Janikas, M. V., Assunçao, R., & Lee, T. H. (2018, November). SKATER-CON: Unsupervised regionalization via stochastic tree partitioning within a consensus framework using random spanning trees. In Proceedings of the 2nd ACM SIGSPATIAL international workshop on AI for geographic knowledge discovery (pp. 33-42).

Cain, B. E., Cho, W., Liu, Y. Y., & Zhang, E. R. (2018). A Reasonable Bias Approach to Gerrymandering: Using Automated Plan Generation to Evaluate Redistricting Proposals. William & Mary Law Review, 59(5).

Chen, M., Kuzmin, K., & Szymanski, B. K. (2014). Community detection via maximization of modularity and its variants. IEEE Transactions on Computational Social Systems, 1(1), 46-65.

Cho, W.K.T. and Liu, Y.Y., 2018. Sampling from complicated and unknown distributions: Monte Carlo and Markov Chain Monte Carlo methods for redistricting. Physica A: Statistical Mechanics and its Applications, 506, pp.170-178.

DeFord, D., Duchin, M., & Solomon, J. (2019). Recombination: A family of Markov chains for redistricting. arXiv preprint arXiv:1911.05725.

Duque, J. C., Ramos, R., & Suriñach, J. (2007). Supervised regionalization methods: A survey. International Regional Science Review, 30(3), 195-220.

Guo, D. (2008). Regionalization with dynamically constrained agglomerative clustering and partitioning (REDCAP). International Journal of Geographical Information Science, 22(7), 801-823.

Mac Donald, K., & Cain, B. E. (2013). Community of interest methodology and public testimony. UC Irvine L. Rev., 3, 609.

Makse, T. (2012). Defining communities of interest in redistricting through initiative voting. Election Law Journal, 11(4), 503-517.

Metric Geometry and Gerrymandering Group. (2022, April 18). GerryChain Version (0.2.20). Retrieved May 27, 2022, from https://github.com/mggg/GerryChain.

Morrill, R. L. (1987). Redistricting, region and representation. Political Geography Quarterly, 6(3), 241-260.

Nagle, J. F. (2019). What criteria should be used for redistricting reform?. Election Law Journal: Rules, Politics, and Policy, 18(1), 63-77.

Pierre-Louis, S. (1995). The Politics of Influence: Recognizing Influence Dilution Claims Under Section 2 of the Voting Rights Act. The University of Chicago Law Review, 62(3), 1215-1241.

Polsby, D. D., & Popper, R. D. (1991). The third criterion: Compactness as a procedural safeguard against partisan gerrymandering. Yale L. & Pol'y Rev., 9, 301.

Stephanopoulos, N. O., & McGhee, E. M. (2015). Partisan gerrymandering and the efficiency gap. U. Chi. L. Rev., 82, 831.

Turner Jr, M. L., & LaMacchia, R. A. (1999). The US census, redistricting, and technology: A 30-year perspective. Social science computer review, 17(1), 16-26.

Webster, G. R. (2013). Reflections on current criteria to evaluate redistricting plans. Political Geography, 32, 3-14.

Winburn, J. (2008). The realities of redistricting: Following the rules and limiting gerrymandering in state legislative redistricting. Lexington Books.