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#### IN THE SUPREME COURT OF WISCONSIN

#### No. 2023AP1399-OA

REBECCA CLARKE, RUBEN ANTHONY, TERRY DAWSON, DANA GLASSTEIN, ANN GROVES-LLOYD, CARL HUJET, JERRY IVERSON, TIA JOHNSON, ANGIE KIRST, SELIKA LAWTON, FABIAN MALDONADO, ANNEMARIE MCCLELLAN, JAMES MCNETT, BRITTANY MURIELLO, ELA JOOSTEN (PARI) SCHILS, NATHANIEL SLACK, MARY SMITH-JOHNSON, DENISE (DEE) SWEET, AND GABRIELLE YOUNG,

#### Petitioners,

GOVERNOR TONY EVERS, IN HIS OFFICIAL CAPACITY; NATHAN ATKINSON, STEPHEN JOSEPH WRIGHT, GARY KRENZ, SARAH J. HAMILTON, JEAN-LUC THIFFEAULT, SOMESH JHA, JOANNE KANE, AND LEAH DUDLEY,

Intervenors-Petitioners,

v.

WISCONSIN ELECTIONS COMMISSION, DON MILLIS, ROBERT F. SPINDELL, JR.,
MARK L. THOMSEN, ANN S. JACOBS, MARGE BOSTELMANN, AND CARRIE RIEPL, IN THEIR
OFFICIAL CAPACITIES AS MEMBERS OF THE WISCONSIN ELECTIONS COMMISSION,
MEAGAN WOLFE, IN HER OFFICIAL CAPACITY AS THE ADMINISTRATOR OF THE
WISCONSIN ELECTIONS COMMISSION; ANDRÉ JACQUE, TIM CARPENTER, ROB HUTTON,
CHRIS LARSON, DEVIN LEMAHIEU, STEPHEN L. NASS, JOHN JAGLER, MARK SPREITZER,
HOWARD L. MARKLEIN, RACHAEL CABRAL-GUEVARA, VAN H. WANGGAARD,
JESSE L. JAMES, ROMAINE ROBERT QUINN, DIANNE H. HESSELBEIN, CORY TOMCZYK,
JEFF SMITH, AND CHRIS KAPENGA, IN THEIR OFFICIAL CAPACITIES AS MEMBERS OF THE
WISCONSIN SENATE,

#### Respondents,

#### WISCONSIN LEGISLATURE;

BILLIE JOHNSON, CHRIS GOEBEL, ED PERKINS, ERIC O'KEEFE, JOE SANFELIPPO, TERRY MOULTON, ROBERT JENSEN, RON ZAHN, RUTH ELMER, AND RUTH STRECK, Intervenors-Respondents.

EXPERT REPORT OF DR. DARYL DEFORD IN SUPPORT OF WRIGHT PETITIONERS' MAP

# Expert Report of Professor Daryl R. DeFord On the Wright Petitioners' Proposed Remedial Map

Friday, January 12, 2023

## I Executive Summary

I was asked by counsel for the Wright Petitioners to analyze their proposed map (the "Wright Map") according to the principles provided in the Wisconsin Supreme Court's decision of December 22, 2023 ("December 22 Decision"), and Drs. Grofman and Cervas' technical specifications letter of December 26, 2023 ("Grofman & Cervas Letter"). Based on my analysis as described in this report, my conclusion is that the Wright Map satisfies all mandatory state and federal districting requirements, performs strongly on nonmandatory traditional districting criteria, and respects neutrality by treating voters in a neutral and symmetric fashion. It therefore improves on the current map that the Court held to be unconstitutional (the "2022 Map").

Following the process outlined in the Court's opinion, I evaluated whether the Wright Map satisfies mandatory districting criteria under state and federal law, beginning with the contiguity requirement that was the basis of the Court's decision. The Wright Map is contiguous according to the definition the Court adopted and addresses the identified constitutional violation without redrawing districts that were already formed entirely of contiguous wards. The Wright Map also satisfies the population-equality requirement. To satisfy the one-person, one-vote principle, state legislative maps in Wisconsin have frequently been constructed to have no districts that deviate by more than 1% from the ideal population. The Wright Map meets this standard. Next, the Wisconsin Constitution requires that assembly districts be "bounded by county, precinct, town or ward lines." The Wright Map complies with this requirement because all of its district boundaries track county, town, and ward lines, and neither its assembly nor senate districts split any wards.

Assembly districts in Wisconsin are also required to be as compact as practicable, and senate districts must consist of convenient territory. The Wright

<sup>&</sup>lt;sup>1</sup> Clarke v. Wisconsin Elections Commission, 2023 WI 79.

Map performs very well on standard measures of compactness, including Polsby-Popper, Reock, and Convex Hull, outperforming the 2022 Map overall. The Wisconsin Constitution also includes a numbering and nesting requirement. I have verified that the senate districts proposed by the Wright Map are formed of triples of adjacent assembly districts and numbered as required by the Wisconsin Constitution. Finally, the Wright Map complies with the Equal Protection Clause and the Voting Rights Act. Because the districts that contain sizable minority populations consisted entirely of contiguous municipal wards in the 2022 Map, they are left unchanged in the Wright Map. No party has suggested that those districts violate the Equal Protection Clause or the Voting Rights Act. Therefore, my analysis shows that the Wright Map satisfies all of the mandatory state and federal districting criteria.

Beyond the required criteria, the Wright Map also performs well on nonmandatory traditional districting criteria, including reducing municipal splits and preserving communities of interest. The Wright Map splits fewer counties than the 2022 Map, does well in preserving municipalities, including splitting fewer towns in the assembly map than the 2022 Map, and splits zero wards. The Wright Map also performs well in keeping together many relevant communities of interest in the state, including federally recognized American Indian Tribal communities, public-school districts, media markets, and the cores of communities identified by the state's People's Maps Commission.

Thus, I conclude that the Wright Map clearly satisfies the preceding mandatory and nonmandatory traditional criteria. Balancing all of these competing and occasionally conflicting criteria is a difficult task, but the Wright Map has been prepared with the assistance of computational redistricting techniques, which allow for optimization while navigating the tradeoffs between conflicting criteria. Drawing on these techniques, the Wright Map is able to achieve excellent performance on metrics related to mandatory and nonmandatory districting criteria.

I further conclude that among the class of acceptable maps, the Wright Map would be a desirable map because it respects and reflects partisan neutrality. Specifically, the Wright Map assembly and senate districts treat equally voters who support each major political party, as measured by widely accepted measures of partisan symmetry. The intuition and normative value behind these measures is that in similar circumstances (usually expressed through statewide vote shares) a symmetric districting plan is one that treats the voters aligned with both parties in the same way. Partisan symmetry is not a proportional representation standard, but rather a natural extension of the majoritarian principle that a minority of

voters should not dominate the majority. In this report, I apply several standard measures of partisan symmetry to a large collection of statewide votes. On each of these measures, the Wright Map demonstrates a significant improvement over the 2022 Map in treating voters from the two major parties more equally. Evaluated across a wide range of elections, the Wright Map returns desirable values on standard metrics of partisan symmetry, is majoritarian on the majority of statewide elections for the past decade, and on the small set of elections where it deviates from this standard, there are examples supporting each party.

Finally, to address some unique features of Wisconsin's political geography and elections, I also formulated an election model trained on Wisconsin's state legislative election returns and used this model to provide an analysis of a likely election under the Wright Map. Under this model, which also takes into account factors related to incumbency and voting trends, the Wright Map performs exceptionally well, as I show in my detailed analysis of the seats-votes curves associated with the Wright Map. The Wright Map is an excellent candidate for adoption to offer voters from both major parties an equal opportunity to translate votes into representation.

The remainder of this report presents a detailed quantitative analysis of the Wright Map to support the conclusions summarized above.

#### II Qualifications

I am an Assistant Professor of Data Analytics in the Department of Mathematics and Statistics at Washington State University. I earned A.M. and Ph.D. degrees in Mathematics at Dartmouth College and also hold a B.S. in Theoretical Mathematics from Washington State University. From 2018 to 2020, I was a postdoctoral associate in the Geometric Data Processing Group in the Computer Science and Artificial Intelligence Laboratory at the Massachusetts Institute of Technology and affiliated with the Metric Geometry and Gerrymandering Group in the Jonathan M. Tisch College of Civic Life at Tufts University. In that role, I had a full-time focus on computational redistricting research.

My mathematical work focuses on applications of combinatorial and algebraic techniques to the analysis of social data and particularly includes the study of statistical sampling techniques for political redistricting problems. This work includes both theoretical design and analysis of algorithms, as well as empirical projects modeling the interactions between districting criteria. My

redistricting work has been published in peer-reviewed journals, including the Harvard Data Science Review, Political Analysis, Statistics and Public Policy, the Journal of Computational Social Science, Physical Review E, and the Society of Industrial and Applied Mathematics Journal on Applied Algebra and Geometry. I have given dozens of presentations on computational redistricting and designed an Independent Activity Period course at MIT, a graduate topics course at WSU, and materials for the American Mathematics Society Engaged Pedagogy Series on computational redistricting. As a postdoc, I helped supervise the Voting Rights Data Institute summer program in 2018 and 2019, and in Summer 2021 I supervised a team of research fellows through the University of Washington's Data Science for Social Good program applying computational redistricting to initial stages of the map-making process.

I have prepared expert reports, amicus briefs, and testimony in redistricting cases, including in this Court's *Johnson* case:

- In 2022, I collaborated with other computational redistricting experts on an amicus brief to the United States Supreme Court in *Allen v. Milligan*, discussing the role of sampling and optimization methods in legal analyses of redistricting plans.<sup>2</sup> This brief was referenced at oral argument and quoted in the Court's opinion in the case. In particular, the Court relied on this brief to reject Alabama's attempt to justify its plan using one of plaintiffs' map studies, concluding that the state's approach was "flawed in its fundamentals," "misconceive[d] the math project that it expects courts to oversee," and "offer[ed] no rule or standard for determining" the state's redistricting choices.<sup>3</sup>
- In 2022, I testified as an expert witness in *Carter v. Chapman* in Pennsylvania's Commonwealth Court. The Pennsylvania Supreme Court relied on the metrics and analysis from my reports and testimony for comparing proposed congressional maps, stating that

<sup>&</sup>lt;sup>2</sup> See Brief for Congressional Redistricting Experts as Amici Curiae Supporting Appellees and Respondents, Allen v. Milligan, 599 U.S. 1 (2023) (Nos. 21–1086, 21–1087).

<sup>&</sup>lt;sup>3</sup> Allen v. Milligan, 599 U.S. 1, 35–36 (2023); see also id. at 107 (Alito, J., dissenting) (noting that the Court's reasoning on this point "relies entirely on an amicus brief submitted by three computational redistricting experts in support of the appellees").

<sup>&</sup>lt;sup>4</sup> See 270 A.3d 444 (Pa. 2022) (discussing Commonwealth Court proceedings).

"we rely upon the analyses performed by Dr. Daryl DeFord, which evaluate all of the submitted plans using the same methods and data sets," and that "[w]e appreciate Dr. DeFord's efforts in this regard as it allows the Court to engage in an apples-to-apples comparison of the plans on each metric."<sup>5</sup>

- In 2021, I prepared two expert reports presented to the Wisconsin Supreme Court for the Citizen Mathematician and Scientists Intervenors-Petitioners in the *Johnson* case.<sup>6</sup>
- In 2021, Dr. Jeanne Clelland, Dr. Beth Malmskog, Dr. Flavia Sancier-Barbosa, and I provided reports and analysis for the 2021 Colorado Independent Legislative Redistricting Commission. Our work was cited by the Commission in its final report supporting its maps, and the Colorado Supreme Court cited our work as evidence that the Commission complied with the legislative requirement to optimize for the number of competitive districts.<sup>7</sup>
- In 2019, I performed computational work and served as a collaborator on an amicus brief to the United States Supreme Court in Rucho v. Common Cause.<sup>8</sup>

I have not been deposed in any legal proceeding. A full copy of my CV is included in Appendix F and contains a list of my publications in the last 10 years. For my work on this matter, I am being compensated at a rate of \$350 per hour. This compensation does not depend in any way on the results of my analysis, the conclusions that I draw, or the eventual outcome of the litigation.

<sup>6</sup> See Expert Report of Dr. Daryl DeFord on Behalf of Intervenors-Petitioners Citizen Mathematicians and Scientists, No. 2021AP001450-OA (Dec. 30, 2021); Rebuttal Expert Report of Dr. Daryl DeFord on Behalf of Intervenors-Petitioners Citizen Mathematicians and Scientists, No. 2021AP001450-OA (Jan. 4, 2022).

<sup>&</sup>lt;sup>5</sup> *Id.* at 462–63.

<sup>&</sup>lt;sup>7</sup> See In re Colo. Indep. Legis. Redistricting Comm'n, 2021 CO 76 ¶¶59-61.

<sup>&</sup>lt;sup>8</sup> See Amicus Brief of Mathematicians, Law Professors, and Students in Support of Appellees and Affirmance, Rucho v. Common Cause, 139 S. Ct. 2484 (2019) (Nos. 18-422, 18-726).

#### III Introduction

This report presents a quantitative analysis of the Wright Map proposed by the Wright Petitioners, according to the principles outlined in the December 22 Decision and the Grofman & Cervas Letter. Specifically, using standard methodologies from political science and computational redistricting, I will demonstrate that the proposed plan complies with mandatory state and federal districting criteria, performs well on additional nonmandatory traditional districting criteria, and strongly satisfies principles of neutrality and partisan symmetry.

The December 22 Decision and the Grofman & Cervas Letter outline a specific set of properties that will be used to compare and evaluate the proposed maps. Some of these properties are evaluated with simple binary tests. For example, given the definition of contiguity described by the Court in its December 22 Decision and the choice of data units agreed to in the Joint Stipulation as to Redistricting Data of December 30, 2023 ("December 30 Data" Stipulation"), checking that each district is contiguous is relatively straightforward. For some of the other criteria, the Court's consultants have specified which measurements are to be reported. For example, for population balance, the Grofman & Cervas Letter asks for the total deviation and the district-by-district difference from the ideal population to be reported, while for boundary preservation it asks for the number of counties or other units that are split and the total number of split pieces for each type of unit. For other criteria, although the Court and its consultants did not specify exactly the measurements to be reported, properties such as compactness and partisan neutrality have wellestablished metrics for measurement that are generally accepted in the scientific literature and regularly relied on by courts.

One of the fundamental difficulties of the redistricting problem is that the various mandatory and nonmandatory criteria cannot all be simultaneously extremized. In assessing individual redistricting plans, it is critical to be mindful of tradeoffs that take place among redistricting criteria. Thus, having access to quantitative and computational methods to evaluate the relevant possibilities is necessary to carry out modern districting analysis. Modern algorithms make the task of searching for good examples from among the space of potential plans much more tractable than naively attempting to enumerate all possible districtings. Many current computational redistricting methods and algorithms operate by combining large changes in plans, intended to explore the possibilities of a given state, with relatively small changes that attempt to extremize a small

set of relevant conditions, all subject to a global set of feasibility constraints. By evaluating large collections of plans that satisfy a set of criteria, combined with local search algorithms near promising, strongly performing plans, we can identify consequences of specific choices in the modeling process and specific ways in which the constraints conflict.

The Wright Map analyzed in this report is a product of exactly this type of modern computational redistricting methodology, achieving the mandatory legal constraints while also considering on-the-ground factors including sensible ways to split counties, cities, villages, and towns as necessary to create a practical plan that treats all Wisconsin citizens fairly. Consistent with the December 22 Decision, the Wright Map satisfies all mandatory redistricting requirements under state and federal law; excels on traditional districting criteria identified in the December 22 Decision; and minimizes political impact, thus exemplifying partisan symmetry and majority rule.

# IV Mandatory Districting Requirements Under State and Federal Law

In this section I analyze the map proposed by the Wright Petitioners and demonstrate that it satisfies the mandatory districting requirements under state and federal law.

# IV.A Contiguity

Article IV, Section 4 of the Wisconsin Constitution requires assembly districts to "consist of contiguous territory" and senate districts to consist of "convenient contiguous territory." The Court's December 22 Decision is unequivocal about the relevant definition of contiguity for analyzing districting plans. As the Court explains, "for a district to be composed of contiguous territory, its territory must be touching such that one could travel from one point in the district to any other point in the district without crossing district lines." The Grofman & Cervas Letter states that "[i]f there are non-contiguous units," parties should "identify which these are and into how many pieces each unit is

<sup>&</sup>lt;sup>9</sup> Wis. Const. art. IV, §§ 4–5.

<sup>&</sup>lt;sup>10</sup> 2023 WI 79, ¶66.

being divided," as well as "[p]rovide a rationale based on a valid state interest for each instance." 11

The Wright Map is contiguous as required and there are no noncontiguous districts. The Wright Map also addresses the identified constitutional violation without redrawing districts that do not contain noncontiguous municipal wards. Thus, the Wright Map leaves in place Senate Districts 3, 4, 6, and 7, the only four current senate districts in the state that do not contain any noncontiguous municipal wards.

Due to the physical geography of the state, there are some districts that require traversing water to connect. The Court's December 22 Decision explains that "certain districts span bodies of water," and that "[t]his does not, by itself, violate the contiguity requirement." The water boundaries recognized by the Court impact Assembly Districts 1, 4, 6, 21, 36, 53, 54, 74, and 90 and Senate Districts 1, 2, 7, 12, 18, 25, and 30. As you can see in Figure 1 below, these water contiguities do not require traversing long diagonals through the water and are supported by the Census water units. Additionally, these water boundaries are consistent with previous Wisconsin redistricting. Note that the Apostle Islands in Lake Superior are not connected to the closest contiguous landmass (in Bayfield County) but are connected instead to Ashland County because the islands are part of the latter county.

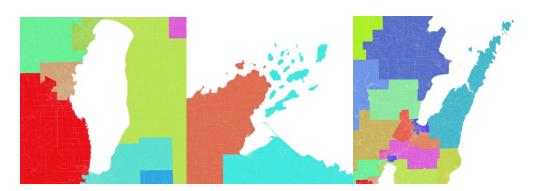


Figure 1: Islands and water contiguity in the Wright Map.

<sup>&</sup>lt;sup>11</sup> Grofman & Cervas Letter at 2.

<sup>&</sup>lt;sup>12</sup> *Id.* ¶27. The Grofman & Cervas Letter cites this discussion as an example of an acceptable rationale for noncontiguous units. *See* Grofman & Cervas Letter at 2.

The Wright Map satisfies the Wisconsin Constitution's contiguity requirement and cures the noncontiguity problem in the 2022 Map without redrawing the four senate districts that do not contain noncontiguous municipal wards.

### IV.B Population Equality

The December 22 Decision specifies that "remedial maps must comply with population equality requirements," and that "[s]tate and federal law require a state's population to be distributed equally amongst legislative districts with only minor deviations."13 Population equality is one of the fundamental principles of American redistricting, frequently referred to as the "one-personone-vote" principle. The Wisconsin Constitution also contains an equalpopulation rule requiring that senate and assembly districts be apportioned "according to the number of inhabitants." <sup>14</sup> In Wisconsin, population deviations for assembly districts have frequently been within 1% of the ideal population, significantly tighter than in most states. Given inaccuracies in Census data (particularly as the data ages<sup>15</sup>), seeking greater population equality is not helpful as a tool for constraining mapmakers' discretion if (as here) there is a separate requirement, applicable to court-ordered remedies, to minimize the map's partisan impact. <sup>16</sup> Thus, the Court's December 22 Decision recognizes that while "courts are held to a higher standard than state legislatures" with respect to population equality, seeking to do better than plus-or-minus 1% deviation, or 2% maximum population deviation, is not required.<sup>17</sup> This tight population

<sup>&</sup>lt;sup>13</sup> 2023 WI 79, ¶64.

<sup>&</sup>lt;sup>14</sup> Wis. Const. art. IV, § 3.

<sup>&</sup>lt;sup>15</sup> See D. DeFord et al., Multi-Balanced Redistricting, 6 J. COMPUTATIONAL SOC. SCI. 923 (2023).

<sup>&</sup>lt;sup>16</sup> See Prosser v. Elections Bd., 793 F. Supp. 859, 866 (W.D. Wis. 1992) (explaining that "[b]elow 1 percent, there are no legally or politically relevant degrees of perfection"); Baumgart v. Wendelberger, No. 01-C-0121, 2002 WL 34127471, at \*2 (E.D. Wis. May 30, 2002) (three-judge court) (reaffirming this conclusion), amended, 2002 WL 34127473 (E.D. Wis. July 11, 2002) (three-judge court); see generally Bernard Grofman, Criteria for Districting: A Social Science Perspective, 33 UCLA L. REV. 77, 88 (1985) (noting that the "talismanic reliance on the equal population standard . . . makes little sense" because, inter alia, the "accuracy of census data is limited, and population equality within less than one percent is illusory").

<sup>&</sup>lt;sup>17</sup> 2023 WI 79, ¶64 (citing *Prosser*'s statement that "[b]elow 1 percent, there are no legally or politically relevant degrees of perfection").

balance means that some counties and municipalities (cities, villages, and towns) must be split in order to achieve this goal.

To operationalize this requirement, the Grofman & Cervas Letter requires parties to "[i]ndicate the total population deviation (overall deviation), and also provide a district-by-district enumeration of the difference between actual and ideal population." Given that the population as reported in the 2020 Census is 5,893,718, the ideal population of an assembly district is 59,532.51 and the ideal population of a senate district is 178,597.52. The Wright Map achieves a maximum population deviation of 1.83% for the assembly plan with a mean deviation of 0.46%. The equivalent figures for the senate plan are 1.19% and 0.23%, as shown in Table 1. The individual district deviations requested by the Grofman & Cervas Letter are given in Tables C.1 and C.2 in the Appendix. The maximum and minimum sizes of the districts in the Wright Map are within the 1% threshold and satisfy the population-equality requirement.

	Maximum	Minimum	Total Deviation	Average Deviation
Assembly	60,077 (0.91%)	58,988 (0.91%)	1,089 (1.83%)	272.9 (0.46%)
Senate	179,681 (0.61%)	177,550 (0.59%)	2,131 (1.19%)	404.0 (0.23%)

Table 1: Population Deviation of the Wright Map.

#### IV.C Political Subdivision Boundaries

Second, the December 22 Decision specifies that "[a]ssembly districts must be . . . bounded by county, precinct, town or ward lines," as required by the Wisconsin Constitution.<sup>20</sup> The Court explained that "[a]s to the 'bounded' requirement, [the Court] considers the extent to which assembly districts split counties, towns, and wards (particularly towns and wards as the smaller political subdivisions), although [it] no longer interpret[s] the requirement to entirely

<sup>&</sup>lt;sup>18</sup> Grofman & Cervas Letter at 2.

<sup>&</sup>lt;sup>19</sup> U.S. Census Bureau, *Wisconsin: 2020 Census*, https://www.census.gov/library/stories/state-by-state/wisconsin-population-change-between-census-decade.html (last visited Jan. 9, 2024).

<sup>&</sup>lt;sup>20</sup> 2023 WI 79, ¶65 (citing Wis. Const. art. IV, § 4). Precincts are a deprecated unit that are no longer specified throughout the state. *See id.* ¶66 n. 28.

prohibit any splitting of the enumerated political subdivisions, as [it] once did."<sup>21</sup> The Grofman & Cervas Letter further specifies that parties are to "[p]rovide the number of counties or other units that are split, and the total number of split pieces for each type of unit," as well as "specify exactly which units are being split and how many times each unit is being split."<sup>22</sup>

The Wright Map satisfies this requirement as the proposed map consists entirely of whole wards, so each district boundary follows at least one such line (county, town, or ward). The assembly districts in the Wright Map split 47 counties, 15 towns, and 0 wards, and the senate districts in the Wright Map split 37 counties, 8 towns, and 0 wards.

To further quantify the extent to which these boundaries align, I measured the percentage, as a function of total perimeter, of the boundary that is composed of county lines, town lines that are not also county boundaries, and ward boundaries that are neither county nor town boundaries. These percentages are reported in Table 2 below. Figure 2 shows an example of a boundary in Assembly District 81 of the Wright Map, where splitting Juneau County was necessary to keep Wisconsin Dells together. The units that are split by the plan, total number of splits created, and pieces of each type as requested by the Grofman & Cervas Letter are addressed in in Sections V.A-C below.

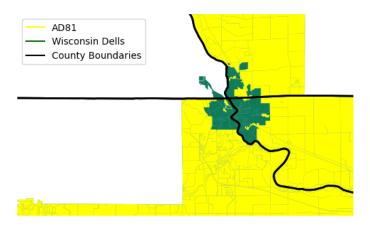


Figure 2: Assembly District 81 follows the boundary of Wisconsin Dells across the county boundary into Juneau, creating one extra county split in order to keep the town together.

<sup>&</sup>lt;sup>21</sup> *Id.* ¶66.

<sup>&</sup>lt;sup>22</sup> Grofman & Cervas Letter at 2.

	County Boundary	Town Boundary	Ward Boundary
Assembly	35%	51%	14%
Senate	38%	49%	13%

Table 2: Percentage of the internal perimeter of the Wright Map that follows county, town, and ward boundaries.

#### IV.D Compactness

The December 22 Decision specifies that assembly districts must be "in as compact form as practicable" and senate districts must be "of convenient contiguous territory," as required by the Wisconsin Constitution.<sup>23</sup> The Court explained that "[c]ompactness is generally defined as 'closely united in territory,' although th[e] court has never adopted a particular measure of compactness."<sup>24</sup> The Grofman & Cervas Letter further states that parties are to "[i]ndicate the compactness metric or metrics employed," and to "provide comprehensive data (i.e., average) for the entire plan as well as detailed data for each district."<sup>25</sup>

There are widely accepted metrics in the political science literature used to evaluate compactness, most of which are normalized ratios between 0 and 1, relating the area of the district, the perimeter of the district, and similar measurements for geometric bounding objects. In this report, I analyze the performance of the Wright Map using four metrics: the Polsby-Popper score, the Reock score, the Convex Hull ratio, and Cut Edges. Because compactness measurements can vary slightly depending on the map projection being used, it helps to know which projection is being used. The measurements in this report are made in the EPSG: 102219 map projection based on the Census block file without water units.

The Polsby-Popper score is a version of what mathematicians call the "isoperimetric ratio," defined as the ratio between a shape's area and the square of its perimeter. In practice, this measurement captures significant information about the relative smoothness of the boundary of a district, and districts following convoluted municipal lines or state boundaries can often receive low values. The Reock score measures the proportion of area of a district to the area

<sup>&</sup>lt;sup>23</sup> See 2023 WI 79, ¶65 (citing Wis. Const. art. IV, § 4).

<sup>&</sup>lt;sup>24</sup> Id. ¶66 (quoting Wis. State AFL-CIO v. Elections Bd., 543 F. Supp. 630, 634 (E.D. Wis. 1982) (AFL-CIO)).

<sup>&</sup>lt;sup>25</sup> Grofman & Cervas Letter at 2.

of the smallest circle that contains it. As with the Polsby-Popper score, this is always a value between 0 and 1, with large values representing a better score. A related measure is the Convex Hull Ratio, which measures the proportion of area of a district to its convex hull in the plane, which is the minimal convex shape that contains the district. The Reock score penalizes districts that are elongated, while the Convex Hull Ratio detects the presence of tendrils or indentations. Each of the first three metrics (Polsby-Popper, Reock, and Convex Hull) addresses a different quality of a given district, and it is possible for a district to score well on one metric but poorly on another.

Tables 3 to 5 below report the Polsby-Popper, Reock, and Convex Hull values for the Wright Map and compare them to the corresponding values for the 2022 Map. Notice that the Wright Map districts score comparably or better than the 2022 Map's districts, which was not challenged for reasons of compactness, and that some of the specific deviations are due to tradeoffs with other factors, such as reducing municipal splits and balancing population.

Polsby-Popper	Min District	Max District	Average
Wright Assembly	.09	.60	.31
2022 Assembly	.05	.57	.24
Wright Senate	.08	.50	.26
2022 Senate	.05	.39	.22

Table 3: Polsby-Popper Compactness.

Reock	Min District	Max District	Average
Wright Assembly	.14	.64	.42
2022 Assembly	.14	.65	.38
Wright Senate	.15	.58	.40
2022 Senate	.13	.59	.39

Table 4: Reock Compactness.

Convex Hull	Min District	Max District	Average
Wright Assembly	.49	.98	.74
2022 Assembly	.29	.92	.71
Wright Senate	.47	.83	.73
2022 Senate	.47	.88	.71

Table 5: Convex Hull Compactness.

In addition, the specific districts that achieve poor individual scores can be explained by factors that are present in all feasible districting plans. As an example, Figure 3 below shows Assembly District 65, which suffers a penalty to its compactness score for following the southern boundary of the City of Kenosha and not splitting the Village of Pleasant Prairie.

According to each of these widely accepted metrics, the Wright Map is a compact plan that easily satisfies the Wisconsin Constitution's requirement that assembly districts be as compact as practicable. In each of the measures, we can see that the average and aggregate values are solid, and the specific districts that achieve poor individual scores can be explained by factors that are present in all feasible districting plans.

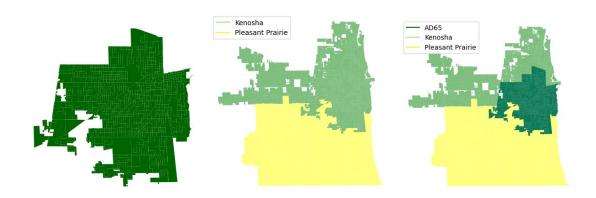


Figure 3: Assembly District 65 follows the noncompact boundary between the City of Kenosha and the Village of Pleasant Prairie. Since the population of Pleasant Prairie is 21,250, it cannot simply be added to Assembly District 65 without compromising population balance.

As these three measures are defined in terms of simple geometric quantities, they achieve their maximum value at the circle, which is not feasible to create out of discrete units like Census blocks. Additionally, circles, unlike hexagons or squares, cannot be used to tile a rectangular region. As a districting plan is an assignment of Census blocks to districts, the line drawer does not have complete control over the boundary shapes of the blocks that make up the plan. A discrete measure of compactness, the Cut Edges score, is one way to account for this fact. The Cut Edges metric measures the number of times adjacent units are separated. Thus, I also evaluate the number of cut edges in the Census-block-level dual graph. This is the only one of my four measures of compactness for which a lower number denotes a more compact plan. The Wright Map has 14,929

cut edges in the assembly map and 8,772 in the senate map compared to 19,196 and 10,785 respectively for the 2022 Map.

Beyond these types of conflicts and state-specific context, compactness measures can also be perturbed by choice of data units, levels of resolution, map projections, and other data science considerations. Thus, strict reliance on any specific metric or cutoff is not likely to offer a one-size-fits-all solution. Instead, the individual values and districts must be analyzed directly. Overall, the performance of the Wright Map across the board as compared to the 2022 Map demonstrates that the Wright Map satisfies the constitutional requirements that assembly districts must be in as compact form as practicable and that senate districts consist of convenient territory, as shown in Figure 4.

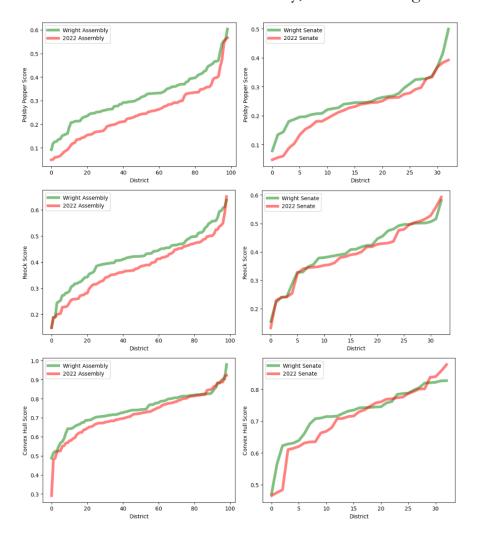


Figure 4: Comparison of compactness metrics between the Wright Map and the 2022 Map. For each plan and score, the compactness values of the districts are sorted from smallest to largest. The left column shows the scores for the assembly, plans in both maps, while the right column shows the scores for the senate maps. The metrics from top to bottom are Polsby Popper, Reock, and Convex Hull.

#### IV.E Numbering and Nesting

The December 22 Decision provides that districts must meet the "numbering and nesting requirements set out in Article IV, Sections 2, 4, and 5" of the Wisconsin Constitution. <sup>26</sup> Specifically, "[a]ssembly districts must be 'nested' within a senate district—that is, 'no assembly district shall be divided in the formation of a senate district." I have verified that the senate districts proposed in the Wright Map are each formed as the union of three adjacent assembly districts, with numbering as required by state law.

# IV.F Federal Law Compliance and Minority Electoral Opportunity

The December 22 Decision requires that "remedial maps must comply with all applicable federal law," including not only the population equality requirement but also the "Equal Protection Clause and the Voting Rights Act of 1965." The Grofman & Cervas Letter specifically asks parties to "[p]rovide any data relevant to [their] assessment of compliance with the Voting Rights Act," including "any replication code required for the analysis of racially polarized voting" and an explanation of the methodology used. <sup>29</sup>

The Wright Map complies with these federal-law requirements. The Wright Map keeps whole Senate Districts 3, 4, 6, and 7, as they are the only senate districts in the state that are composed entirely of contiguous wards. These four districts also happen to include the only districts in Wisconsin that contain sizable minority populations, namely Senate Districts 3, 4, and 6, and Assembly Districts 8, 9, 10, 11, 12, 16, 17, and 18, all of which are in Milwaukee County. It is my understanding that no party has contended that there is any

<sup>&</sup>lt;sup>26</sup> 2023 WI 79, ¶65.

 $<sup>^{27}</sup>$  Id. ¶65 n. 27 (quoting Wis. Const. art. IV, § 5). The Court also notes that by statute, there must be "'33 senate districts, each composed of 3 assembly districts." Id. (quoting Wis. Stat. § 4.001).

<sup>&</sup>lt;sup>28</sup> *Id.* ¶67.

<sup>&</sup>lt;sup>29</sup> Grofman & Cervas Letter at 2.

issue under the Voting Rights Act or the Equal Protection Clause with any of these existing districts.

The other districts composed entirely of contiguous wards that the Wright Map leaves unchanged from the 2022 Map are Senate District 7 and Assembly Districts 7, 19, 20, and 21. These districts do not contain sizable minority populations. In these assembly districts, the percentage of non-Hispanic white voting-age population varies between 65.3% and 80.1%, and it is 78.6% in Senate District 7.

# V Other Traditional Districting Criteria

Beyond the mandatory criteria addressed in Section IV, the December 22 Decision states that the Court "will consider other traditional districting criteria not specifically outlined in the Wisconsin or United States Constitution, but still commonly considered by courts tasked with formulating maps," including "reducing municipal splits and preserving communities of interest." The Court explained that "[t]hese criteria will not supersede constitutionally mandated criteria, such as equal protection requirements, but may be considered when evaluating submitted maps." <sup>31</sup>

In this section I analyze the proposed maps using nonmandatory traditional districting criteria, demonstrating that the Wright Map performs extremely well on commonly accepted measurements of these principles, particularly compared to the 2022 Map.

#### V.A Reducing County Splits

As noted, the Grofman & Cervas Letter specifies that parties are to "[p]rovide the number of counties or other units that are split, and the total number of split pieces for each type of unit," as well as "specify exactly which units are being split and how many times each unit is being split."<sup>32</sup> It is not

<sup>&</sup>lt;sup>30</sup> 2023 WI 79, ¶68 (citing *AFL-CIO*, 543 F. Supp. at 636 (comparing municipal splits) and *Baldus v. Members of Wis. Gov't Accountability Bd.*, 849 F. Supp. 2d 840, 856-57 (E.D. Wis. 2012) (three-judge court) (considering whether district lines disrupted communities of interest)).

<sup>&</sup>lt;sup>31</sup> *Id.* (citing *AFL-CIO*, 543 F. Supp. at 636).

<sup>&</sup>lt;sup>32</sup> Grofman & Cervas Letter at 2.

possible to construct a constitutional plan that splits no counties because some counties are larger than the ideal population of a senate or assembly district. The Wright Map performs well on this metric in relation to prior maps. The Wright assembly map splits 47 of the 72 counties in Wisconsin into 153 extra pieces, and the Wright senate map splits 37 counties into 74 extra pieces. The complete list of splits and pieces is included in Tables C.3 to C.6 in the Appendix. These values are better than those for the 2022 assembly map, which split 53 counties into 159 extra pieces, and the 2022 senate map, which split 42 counties into 73 extra pieces respectively. It also improves on the enacted map from the previous decade, which split 58 counties in the assembly map and 46 counties in the senate map.

#### V.B Reducing Municipal Splits

The December 22 Decision also identifies "reducing municipal splits" as a traditional districting criterion that courts also consider.<sup>33</sup> It is not possible to construct a constitutional plan that splits no municipalities because of the population balance requirement, so there must be some splits in any feasible plan. In addition to aligning the assembly districts so that they (as well as the resulting senate districts) are bounded by county, town, and ward lines, the Wright Map also attempts to minimize the number of municipalities that are split, and performs well specifically with respect to town splits. The Wright assembly map splits 52 municipalities into 89 extra pieces. Of these split units, 15 are towns, split into 17 extra pieces. The Wright senate map splits 34 municipalities into 52 extra pieces, including 8 towns and 10 extra town pieces. These results are comparable to the 2022 Map, as the 2022 assembly map split 16 towns and the 2022 senate map also split 8 towns. Note that these figures are conservative because I count municipal pieces with no population as pieces. In Tables C.3 to C.6 in the Appendix, I report the specific municipalities and pieces split by this plan.

### V.C Minimizing Ward Splits

The Wright Map splits no wards, as understood under paragraph 8 of the December 30 Data Stipulation. Minimizing ward splits is of particular importance to election administration, as it prevents the need for additional

<sup>&</sup>lt;sup>33</sup> 2023 WI 79, ¶68.

multiple ballot types and the resulting overhead and complexity. It is not possible to perform better on this measure than the Wright Map.

#### **V.D** Preserving Communities of Interest

The Grofman & Cervas Letter requires parties to "specify the size and geographic location of any communities of interest identified and the degree to which these communities of interest have been split across multiple districts."<sup>34</sup>

I understand preserving communities of interest to be an appropriate consideration in selecting between plans that comply with legal requirements. I considered five different types of communities of interest that are often analyzed in the literature. To measure the amount of preservation of communities, I evaluated the number of splits, as well as the uncertainty of membership and total effective splits measures recently introduced to provide a more refined analysis of community preservation.<sup>35</sup> For each of these metrics, a smaller number is better.

First, one way to measure the preservation of communities of interest is to count the number of political subdivision splits. As discussed above, the Wright Map performs well in respecting county, municipal, and ward lines.

Second, I examined Tribal communities. There are 11 reservations for federally recognized Indian Tribes in Wisconsin: (1) the Bad River Band of the Lake Superior Chippewa Indians of the Bad River Reservation; (2) the Forest County Potawatomi Community; (3) the Ho-Chunk Nation; (4) the Lac Courte Oreilles Band of Lake Superior Chippewa Indians; (5) the Lac du Flambeau Band of Lake Superior Chippewa Indians of the Lac du Flambeau Reservation; (6) the Menominee Indian Tribe; (7) the Oneida Nation; (8) the Red Cliff Band of Lake Superior Chippewa Indians; (9) the Sokaogon Chippewa Community; (10) the St. Croix Chippewa Indians; and (11) the Stockbridge Munsee Community. Of these, 10 are entirely contained in a single assembly district in the Wright Map, so these communities are not split at all. The exception is the Ho-Chunk Nation, which has widely dispersed and discontiguous components (spread across Dane, Jackson, Juneau, Monroe, Sauk, Shawano, and Wood Counties) that would be

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<sup>&</sup>lt;sup>34</sup> Grofman & Cervas Letter at 2.

<sup>&</sup>lt;sup>35</sup> See S. Chen, S. Wang, B. Grofman, R. Ober, K. Barnes, and J, Cervas, *Turning Communities of Interest into a Rigorous Standard for Fair Redistricting*, 18 STAN. J. CIV. RIGHTS & CIV. LIB., 101-190 (2022).

difficult or impossible to include in a single compact, contiguous, population balanced district. The Wright Map does a better job of preserving these communities than the 2022 Map, as summarized in Table 6 below for the 10 Tribal communities besides the Ho-Chunk Nation. For these and the following communities, I report two additional measures beyond the simple number of community units that are split. These are the Uncertainty of Membership metric and the Effective Splits score.<sup>36</sup> These metrics are designed to help assess the amount of harm caused by a split, recognizing that in terms of obtaining representation, a group may suffer a relatively less significant harm if only a small piece of the community is separated into another district than if the entire community is cut in half.

AMIN Land	Total Splits	Uncertainty of Membership	Effective Splits
Wright	0	0	0
Assembly			
2022	4	2.5	2.6
Assembly			
Wright	0	0	0
Senate			
2022 Senate	2	0.9	0.7

Table 6: Comparison of splits of American Indian reservations between the Wright Map and the 2022 Map.

Third, I examined school districts. When a school district is contained wholly within an assembly or senate district, advocacy for similarly situated students and families is simplified. The Wright Map outperforms the 2022 Map on all three splitting metrics with respect to school districts, as shown in Table 7.

School Districts	Total Splits	Uncertainty of Membership	Effective Splits
Wright Assembly	272	172.9	142.1
2022 Assembly	276	194.4	161.3
Wright Senate	192	104.3	76.1
2022 Senate	199	113.8	84.5

Table 7: Comparison of splits of school districts between the Wright Map and the 2022 Map.

<sup>36</sup> See id.

Fourth, I analyzed Wisconsin's television markets. Media markets are natural regions for political advertising and campaigning. Wisconsin contains part or all of eight Designated Market Areas: Milwaukee, Green Bay/Appleton, Madison, La Crosse/Eau Claire, Wausau/Rhinelander, Minneapolis/St. Paul (MN), Duluth (MN)/Superior, and Marquette (MI). The Wright Map again outperforms the 2022 Map with respect to these splitting metrics as shown in Table 8.

Media	Total Splits	Uncertainty of Membership	Effective Splits
Markets			
Wright	7	24.7	99.5
Assembly			
2022	7	24.9	100.9
Assembly			
Wright	7	15.54	31.1
Senate			
2022 Senate	7	15.8	32.0

Table 8: Comparison of splits of media markets between the Wright Map and the 2022 Map

Finally, I considered the communities identified by the People's Maps Commission. Wisconsin gathered information this redistricting cycle about the existence and location of communities of interest using modern technological tools that allowed citizens to submit their own community outlines. The People's Maps Commission facilitated the process. However, aggregating the submitted outlines of a particular community's borders often resulted in sprawling regions that were too large to fit inside an entire district. Unlike the reservations, school districts, and media markets which had sharp, well-defined boundaries, these communities were less structured. The People's Maps Commission's raw data represents counts, per Census block, of how often a citizen placed that block inside a particular community. In order to focus on a community's core, I determined the block that had been selected the most times for it and defined the core to be all blocks that had been selected at least 25% as often as this most

popular block. The splits and community preservation metrics of these cores are presented in Table 9 below.

People's Map	Total Splits	Uncertainty of Effective Spli			
Commission		Membership			
Wright Assembly	35	56.3	67.1		
2022 Assembly	35	58.1	70.0		
Wright Senate	33	29.5	23.9		
2022 Senate	35	32.1	28.3		

Table 9: Comparison of splits of PMC core communities of interest between the Wright Map and the 2022 Map.

Across all of these types of communities, the Wright Map outperforms the 2022 Map, providing quantitative evidence that it successfully preserves communities of interest.

# VI Political Neutrality

The Wright Map cures the identified contiguity problem, satisfies the mandatory state and federal districting criteria, and performs well on nonmandatory traditional redistricting criteria. In addition to these requirements, the Court's December 22 Decision states that the Court "will consider partisan impact when evaluating remedial maps." The Grofman & Cervas Letter further requires parties to "specify which metrics were used to estimate the degree to which a map satisfies partisan neutrality," and to "submit any partisan or election data utilized in determining political neutrality," as well as "any replication code necessary for reproducing the results of simulation/ensemble analyses if that methodology has been employed." <sup>38</sup>

Applying my model, I conclude that the Wright Map minimizes partisan impact by respecting partisan symmetry and majority rule. I also include my

<sup>&</sup>lt;sup>37</sup> 2023 WI 79, ¶69.

<sup>&</sup>lt;sup>38</sup> Grofman & Cervas Letter at 3.

replication code in Appendix B to facilitate apples-to-apples comparisons of each party's map submission using the election model described herein.

#### VI.A The Partisan Symmetry Standard

The problem of determining whether a given districting plan treats voters belonging to different groups evenhandedly has been studied extensively, and many quantitative measures have been designed to address this question. In this section, I explain and apply measures of partisan symmetry, the dominant perspective from the political science literature, to analyze the neutrality of the Wright Map.

A large body of political science literature over the past several decades has focused on the concept of partisan symmetry. This standard is "highly intuitive, deeply rooted in history, and accepted by virtually all social scientists," and "[t]ests for partisan symmetry are reliable, transparent, and easy to calculate without undue reliance on experts or unnecessary judicial intrusion on state redistricting judgments." Indeed, "social scientists have long recognized partisan symmetry as the appropriate way to define partisan fairness," and "for many years such a view has been virtually a consensus position of the scholarly community."

The intuition is that a fair districting plan or system is one in which voters affiliated with the two major parties would be treated equally if the overall partisanship of the state were reversed, in the sense that they would obtain equal representation in that scenario. That is, if a map would give one party a 9-seat advantage in the legislature with a 52-48 statewide vote share, then a plan is symmetric at this margin if it would give the other party a 9-seat advantage in the case of a 48-52 statewide vote share. More generally, a plan satisfies the partisan symmetry standard if it is symmetric at all margins. In some ways, this standard asks for too much, however, as the relevant potential vote percentages rarely include values that are too far away from 50-50. We cannot know if the symmetry standard would play out with an 80-20 margin if no election has generated those

<sup>&</sup>lt;sup>39</sup> Brief of Heather Gerken, Jonathan N. Katz, Gary King, Larry J. Sabato, and Samuel S.-H. Wang as Amici Curiae in Support of Appellees at 4, Gill v. Whitford, 138 S. Ct. 1916 (2018) (No. 16-1161).

<sup>&</sup>lt;sup>40</sup> Bernard Grofman & Gary King, *The Future of Partisan Symmetry as a Judicial Test for Partisan Gerrymandering After* LULAC v. Perry, 6 ELECTION L.J. 2, 6 (2007).

results in the state. This is particularly true for the present case, given that Wisconsin is a particularly competitive state, as discussed below.

The partisan-symmetry standard "makes no assumptions about the voting behavior of individual voters but simply assesses how a given plan translates votes into seats." <sup>41</sup> As such, "[s]ymmetry tests do not mandate proportional representation or require a particular ratio of seats to votes. They merely measure whether members of both parties have a chance to translate votes into seats in the same way." <sup>42</sup>

There are several summary metrics related to partisan symmetry that are used in the political science literature to evaluate the partisan fairness of a plan. These include the *partisan bias* score, the *mean median* score, the *efficiency gap*, the *declination score*, and simple statistical tests such as the *lopsided wins* metric. <sup>43</sup> Almost all of these scores begin by constructing a *seats-votes curve* to represent the relationship between the votes cast and the representation won by each party. For a single statewide election, we can construct its seats-votes curve by starting with a pair of axes, where the horizontal axis represents the statewide vote share for party A and the vertical axis represents the number of legislative seats won by party A in that election (determined district-by-district also using the statewide election). A single election corresponds to a single point on these axes. Figure 5 shows this point for the 2020 Presidential election overlaid on the Wright assembly map as compared to the 2022 assembly map. The vote percentages in

<sup>&</sup>lt;sup>41</sup> Brief of Heather Gerken et al. at 14.

<sup>&</sup>lt;sup>42</sup> *Id.*; see also id. at 21.

<sup>&</sup>lt;sup>43</sup> See Samuel S.-H. Wang: Three Practical Tests for Gerrymandering: Application to Maryland and Wisconsin, 15 ELECTION L.J., 367 (2016).

both plots are the same, with the Democratic candidate narrowly prevailing, but the seat percentages are dramatically different.

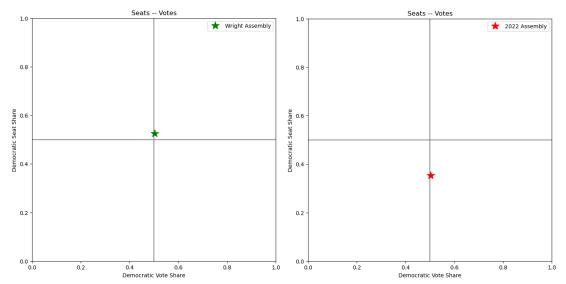


Figure 5: The seats-votes points corresponding to the to the 2020 U.S. Presidential election overlaid on the Wright (left) and 2022 (right) assembly maps.

The statewide vote share in the chosen election (here, the 2020 Presidential election) gives us a *starting point* to construct the rest of a seats-votes curve. One common approach to add more points to the curve is to use the assumption of uniform linear swing, whereby we extrapolate values by adjusting the voting percentages equally in each district to cover the full range of possible vote shares. This curve is called a seats-votes curve for the districting plan, as it represents a model of the relationship between statewide vote share and legislative representation under the given map. This creates the characteristic "stairstep" shape shown in Figure 6 below, where the uniform swing curve is extrapolated from the 2020 presidential election. One way to evaluate the symmetry of such a curve is to reflect, or fold, it around the 50/50 point and measure the gap between the two curves formed this way. This is a direct measure of symmetry demonstrated for this example in Figure 7 below. In that

figure, the blue line is the same as the seats-votes curve from Figure 6 and the red line is the reflection or fold around the central point.

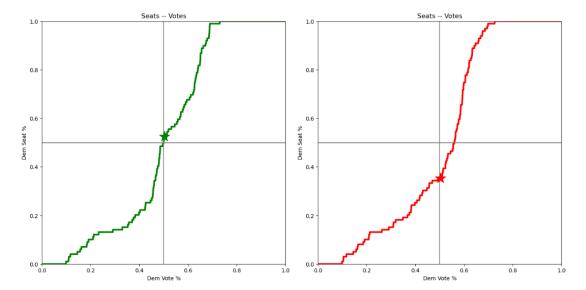


Figure 6: Seats-votes curve from uniform swing applied to the 2020 U.S. Presidential election overlaid on the Wright (left) and 2022 (right) assembly maps.

Several of the partisan symmetry statistics associated with this election data can then be read off of this curve. For example, the *mean-median score* is the horizontal distance from the curve to the 50/50 point, while the *partisan bias* is the vertical distance. A more complex measure of partisan symmetry is to evaluate the area of the difference between the curve and its reflection around the 50/50 point. Particularly when restricted to a small potential range of vote shares near 50 percent, this measure directly captures deviations from symmetry in reasonable election estimates. This measure corresponds to computing the area of the shaded gray regions below.

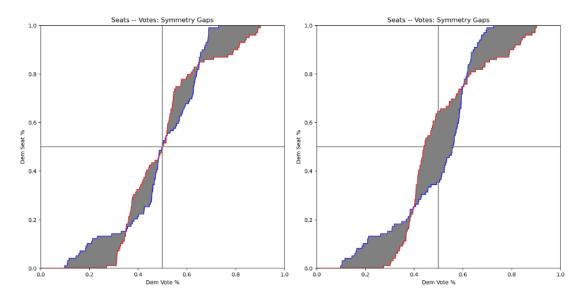


Figure 7: Reflected seats-votes curves for the 2020 U.S. Presidential election overlaid on the Wright (left) and 2022 (right) assembly maps. The gray shaded area between the curves is the asymmetry between the two parties. A smaller gray area, particularly near 50/50, as demonstrated in the Wright Map, is a desirable mark of symmetric treatment.

The other metrics are more independent from seats-votes curves fit to specific elections. For example, the *efficiency gap* measures the difference in the percentage of wasted votes for each party (using an election's single, real-world outcome and a districting plan). The *lopsided wins* metric measures the difference in vote margin between the two parties in the districts that they win in an election, while the *declination* measures the difference in slope between the plot of sorted vote shares of individual districts won by each party.

We can also use the seats-votes axes set-up to consider simple majoritarian measures for context.<sup>44</sup> Viewed on the same axes as the seats-votes discussion above, a majoritarian standard for an election simply maximizes the likelihood that an election's actual location would be in either the first (upper-right) or third (lower-left) quadrants. Requiring this of all the points across the entire seats-votes curve similarly constrains the entire curve to fall into those same two quadrants. A majoritarian standard can be viewed as a less demanding symmetry metric, where the only concern is whether a party that receives a majority of the vote share is rewarded with a majority of the legislative seats. As with the other measures, this majoritarian measure does not require any sort of proportional representation; indeed, a plan that awards a monopoly to either party that

<sup>&</sup>lt;sup>44</sup> See Daryl DeFord et al., Implementing Partisan Symmetry: Problems and Paradoxes, 31 POL. ANALYSIS 305 (2023).

achieves a majority of the vote would satisfy this principle (this describes how we elect governors and attorneys general, for example).

#### VI.B The Partisan Symmetry of the Wright Map

The Wright Map is evenhanded according to these plots and metrics, particularly when compared with the 2022 Map, and the Wright Map shows that it is possible to correct the asymmetries of the previous map while still complying with all mandatory districting requirements and performing well on nonmandatory districting criteria. I began analyzing the partisan symmetry of the Wright Map using a collection of 19 statewide elections from 2012 to 2022. It is common to use statewide elections as an exogenous starting point for evaluating legislative elections because they allow different maps to be compared with the same underlying vote data without needing to account for uncontested races or incumbency effects, which are addressed in Section VI.C below. Wisconsin statewide elections are some of the most competitive in the country. Wisconsin is one of only a few states whose U.S. Senators were from different parties for the entirety of the previous redistricting cycle, and also one of the few states where both parties are represented in statewide elected executive office. The presidential vote totals have also been very close, with two-party vote margins of less than one percentage point—and in opposite directions—in the last two cycles (with the same Republican candidate narrowly prevailing in 2016 and narrowly losing in 2020). This makes Wisconsin, at least from a statewide perspective, almost the definitive example of a swing state.

I analyzed 19 statewide general elections from 2012 to 2022 in Wisconsin, summarized in Table 10. Each of these elections features the same two candidates, who are often well-known and well-funded, in every one of Wisconsin's roughly 7,000 wards, which allows for evenhanded comparisons. These elections have two-party Democratic vote shares of between 46.8% and 55.4%, with over half the elections having a margin of less than 4% and a total of 7 elections won by Republicans and 12 won by Democratic candidates. The support of these elections near 50/50 provides an excellent opportunity to evaluate districting plans overlaid on this data.

Office	Year	Winner	Margin %
Governor	2022	D	3.4
U.S. Senate	2022	R	1.0
Secretary of State	2022	D	0.3
Treasurer	2022	R	1.5
Attorney General	2022	D	1.3
U.S. President	2020	D	0.6
Governor	2018	D	1.1
U.S. Senate	2018	D	10.8
Secretary of State	2018	D	5.6
Treasurer	2018	D	4.2
Attorney General	2018	D	0.7
U.S. President	2016	R	0.8
U.S. Senate	2016	R	3.5
Governor	2014	R	5.7
Secretary of State	2014	D	3.9
Treasurer	2014	R	4.4
Attorney General	2014	R	6.3
U.S. President	2012	D	7.0
U.S. Senate	2012	D	5.7

Table 10: Statewide elections in Wisconsin, 2012-2022.

When statewide elections are overlaid on the 2022 Map and the 2011 Map used in the preceding decade, these same close election counts turn into overwhelming advantages for the Republican Party. For example, while President Biden won the 2020 Presidential vote in Wisconsin by a two-party vote margin of 50.3/49.7, he carried only 35/99 assembly districts and 11/33 senate districts in the 2022 Map. Similarly, while Governor Evers won a narrow majority of all votes cast in the 2022 gubernatorial election, he carried only 39/99 assembly districts and 13/33 senate districts. Both of those values are closely reflected in the actual representation in the state legislature, which currently has a 64-to-35 Republican majority in the Assembly and a 22-to-11 Republican supermajority in the Senate. If these had been legislative house votes, this would reflect a large failure under the majoritarian principle, as the political party with a minority vote share won a majority of the representation.

The majoritarianism of the Wright Map as compared to the 2022 Map with respect to these elections is summarized in Table 11 below, which shows whether the winner of the statewide election would have carried a majority of assembly or senate districts in the Wright Map versus the 2022 Map. Notice that the Wright Map is majoritarian with respect to most of the elections and deviates from the majority in favor of both parties, while the 2022 Map is majoritarian with respect to less than half of the elections and always deviates in favor of the Republican party. It is reasonable to expect that a map that treats voters from each party equally would behave much more like the Wright Map than the 2022 Map.

Office	Year	Winner	Wright Assembly	2022 Assembly	Wright Senate	2022 Senate
Governor	2022	D	Y	N	Y	N
U.S. Senate	2022	R	N	Y	N	Y
Secretary of						
State	2022	D	Y	N	Y	N
Treasurer	2022	R	N	Y	Y	Y
Attorney						
General	2022	D	Y	N	Y	N
U.S.						
President	2020	D	Y	N	Y	N
Governor	2018	D	N	N	N	N
U.S. Senate	2018	D	Y	Y	Y	Y
Secretary of						
State	2018	D	Y	N	N	N
Treasurer	2018	D	Y	N	N	N
Attorney						
General	2018	D	N	N	N	N
U.S.						
President	2016	R	Y	Y	Y	Y
U.S. Senate	2016	R	Y	Y	Y	Y
Governor	2014	R	Y	Y	Y	Y
Secretary of						
State	2014	D	Y	N	Y	N
Treasurer	2014	R	Y	Y	Y	Y
Attorney						
General	2014	R	Y	Y	Y	Y
U.S.						
President	2012	D	Y	N	Y	N
U.S. Senate	2012	D	Y	N	Y	N
Total						
Majoritarian			15	8	14	8

Table 11: Majoritarianism of the Wright Map and 2022 Map over 19 statewide elections from 2012 to 2022. The Wright Map is majoritarian with respect to a majority of the elections and deviates from majoritarianism in both directions.

Continuing on to form the seats-vote plot for these elections also demonstrates the asymmetry in treatment between the maps. Figure 8 shows that the green points for the Wright Map are clustered near the 50/50 point and, as suggested by Table 11 above, are predominantly in the majoritarian quadrants. Reflecting the points around 50/50, we can observe the symmetry directly, particularly with linear curves fit to the data. These are shown for the four maps in Figure 9 below.

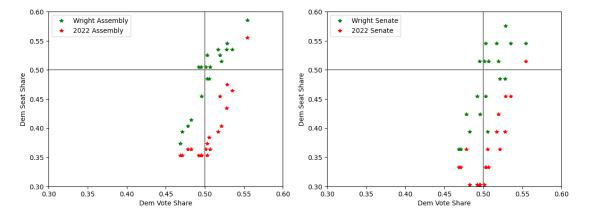


Figure 8: Seats-votes plots for 19 statewide elections for the Wright map and the 2022 map.

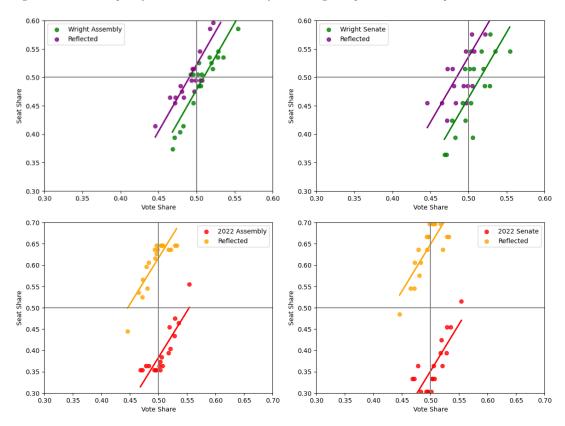


Figure 9: Reflected linear seats-votes curves for 19 statewide elections for the Wright map and the 2022 map.

Computing the uniform swing to build out full seats-votes curves for each of the elections also demonstrates the relatively symmetric nature of the Wright Map. Figure 10 below shows each of the seats-votes curves on a single axis for each chamber and highlights the consistency of the Wright Map in achieving symmetric results across a wide variety of election inputs. This figure shows that either political party could win a majority of seats in either chamber if the statewide vote were tied. This symmetry is particularly clear in comparison to the 2022 Map, as shown in Figure 11, which deviates significantly from symmetry just as consistently across the statewide elections. In particular, these seats-votes curves show that, under the 2022 Map in a tied statewide election, the Democratic candidates would have won between 19 and 29 fewer assembly districts and between 5 and 13 senate districts than Republicans would have won. And in most elections in this period, to win a majority of assembly or senate districts under the 2022 Map, Democrats would have had to win at least 55% of the statewide vote.

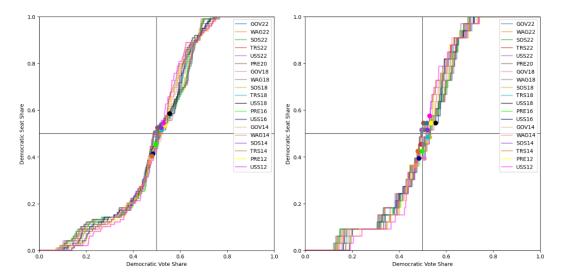


Figure 10: Seats-votes curves for all 19 elections for the Wright Map. Both the assembly map (left) and the senate map (right) are quite symmetric near the 50% vote share values.

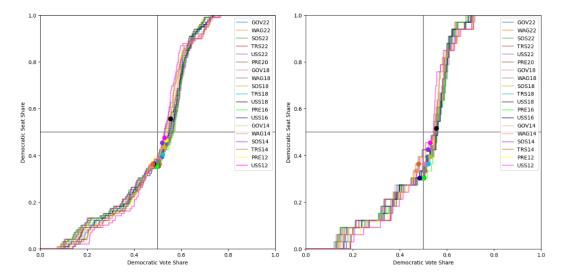


Figure 11: Seats-votes curves for all 19 of the elections for the 2022 Map. Both the assembly map (left) and senate map (right) differ significantly from symmetry and majoritarianism near the 50% vote share values.

We can also use these same elections to evaluate the partisan symmetry metrics for the plans, recalling that the idealized values of the metrics are zero, so scores that are smaller in absolute value are closer to achieving equal treatment of voters. The scores are consistently oriented so that negative values reflect Republican-favoring plans and positive values reflect Democratic-favoring plans. For each of the scores we see that the Wright Map attains values that are significantly closer to the ideal than the 2022 Map, demonstrating that it treats voters from the two major parties more symmetrically. Additionally, for each of the metrics, except lopsided wins, the Wright Map achieves at least one positive

value and one negative value, meaning that there is at least one actual election that occurred where the Wright Map would have favored each party. This stands in stark contrast to the 2022 Map, which always favored the Republican party. As for the lopsided wins metric, due to the preservation of the highly clustered Democratic districts in Milwaukee, there are several districts with a much larger Democratic vote margin than is possible for Republican voters, who are more diffuse throughout the state. Thus, the lopsided wins metric is heavily impacted by this geographic clustering.

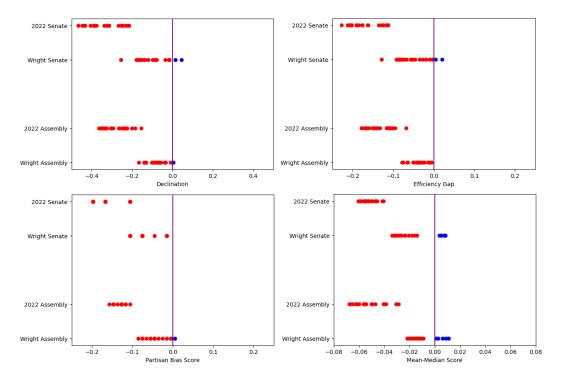


Figure 12: Comparison of partisan symmetry metrics for the 19 statewide elections under all four maps.

Though the Wright Map scores as Republican-favoring on some of these metrics, even for elections in which it would have achieved a majoritarian outcome, this does not mean that it is necessarily an imbalanced or asymmetric plan. Rather, this is a function of using exogenous statewide elections to evaluate the map. In Section VI.C, I will demonstrate that the inclusion of factors left out of an analysis that uses only statewide elections shows that the Wright Map actually scores even better on these measures of symmetry than is suggested by the already small magnitude values presented in Figure 12.

#### VI.C Additional Metrics

The metrics evaluated above each use statewide vote totals from offices like President, U.S. Senator, and Governor—all of whom are on the ballot in every ward in Wisconsin—as a starting point for computing seats-votes curves and other partisan-symmetry statistics. This is because the exogenous nature of statewide elections is useful for overcoming some of the limitations of state legislative election data, including incumbency and uncontested seats. However, the impact of these factors is significant, particularly given the imbalance between the number of legislators from each party under the current plan.

A first observation is that not all statewide elections in the same year are equally probative for understanding and modeling legislative vote share. However, over the past decade, the correlation between precinct-by-precinct votes in contested elections and votes in the corresponding presidential election has strengthened significantly, as shown in Figure 13 below. The top row shows the ward-level Democratic vote-share in presidential elections along the horizontal axis and the Democratic vote-share in assembly races on the vertical axis, across contested assembly elections. The bottom row shows similar information for vote counts rather than percentages. The increase in correlation is striking and strongly suggests that more recent presidential elections offer significantly more explanatory power for legislative votes. The increase in correlation appears consistent across races, but as expected there are some differences between candidates for different offices even on the same ballot.

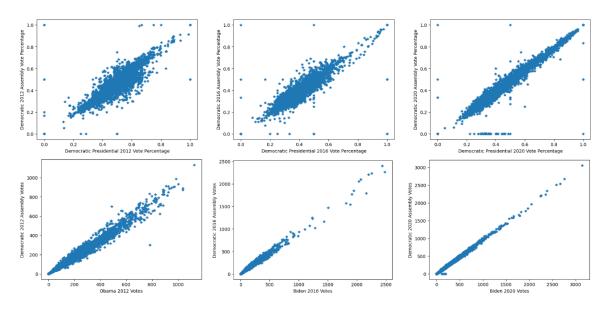


Figure 13: Correlation between presidential vote percentage (top row) and vote counts (bottom row) and assembly votes for (from left) 2012, 2016, and 2020.

Second, even with this strong correlation in recent years, a more accurate vote model can be constructed by considering incumbency advantages. The next figure shows that even in 2020, which had the strongest relationship between presidential and assembly votes, incumbency had a significant impact on outcomes at the ward level. The points in the plot represent ward-level vote shares and the points are colored by whether there is a Republican incumbent (red), Democratic incumbent (blue), or no incumbent (gray). There is a noticeable and unsurprising deviation from the trend line, with wards represented by a Democratic incumbent having a larger Democratic vote share than those without, using the Presidential election as a baseline. This is particularly impactful for the current analysis in Wisconsin, since there is a large discrepancy between the number of Republican incumbents and the number of Democratic incumbents in the next election. Thus, evaluating a districting plan for symmetry on the basis of statewide elections without considering incumbency may lead to unrealistic conclusions about the likely outcomes of a given map, as there is a distinct advantage at the ward level for incumbent representatives.

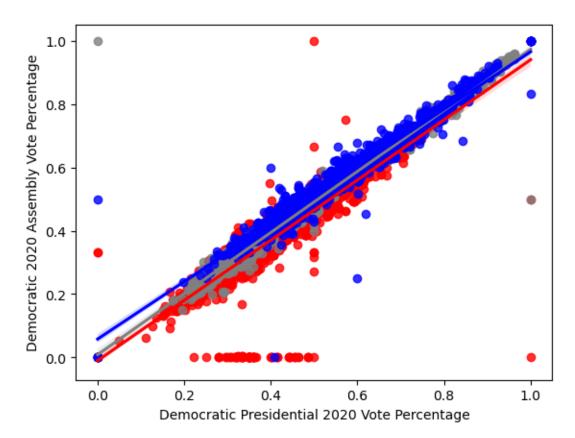


Figure 14: Democratic vote percentage in contested assembly elections in 2020, with points colored by the party of the incumbent.

Another aspect of incumbency to consider is that when district lines change, there are two types of potential relationships between incumbents and the wards they are running to represent. A legislator may be an incumbent in a ward that has changed districts, so while they still benefit from organization and the office, the voters in the ward that the legislator is newly seeking to represent do not necessarily have a history with the candidate. We might expect a smaller incumbency bonus in this case, compared to a ward that the candidate actually represented in the previous assembly. The 2022 election gives us some data to address the question of the size of this difference, as the election was carried out under the 2022 Map with different lines than in the previous 2020 election. The difference in contribution to vote share between incumbents who previously represented a ward and those who did not is statistically significant when used as a regression predictor alongside 2022 general election returns, 45 with approximately double the impact on the legislative vote percentage. Given the scope of the contiguity problems in the 2022 Map that must be remedied, it is likely that many more potential incumbents will find themselves impacted by this issue, as significant changes to the districts may be required to make them constitutional.

Third, while Figure 14 shows that there is an increasingly strong relationship between presidential vote returns and votes for legislative representatives, there are also statewide shifts in the geography of voting behavior that go beyond polarization of already partisan regions. The top row of Figure 15 below shows the Democratic vote-shares in the 2022 Governor, 2020 President, and 2022 U.S. Senate elections, which look quite consistent with many other statewide elections over the previous decade. The bottom row shows how much the vote margin changed in each ward between the 2018 election and the 2022 election for Governor. Darker blue regions represent areas where there was a larger Democratic shift and red regions correspond to Republican shifts. This margin shift is the difference between the more recent ward-level Democratic vote margin and the same values from the previous election. The trend of increasingly Democratic suburbs (and increasingly Republican voting in some rural wards in western Wisconsin) is not particularly well captured by the vote structure of statewide general elections yet. For forward-looking modeling and

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<sup>&</sup>lt;sup>45</sup> See John Johnson, Incumbency Advantage in the 2022 Wisconsin Assembly Election, MARQUETTE UNIV. (Apr. 12, 2023), https://law.marquette.edu/facultyblog/2023/04/incumbency-advantage-in-the-2022-wisconsin-assembly-election.

analysis, this fact is another important term to consider when evaluating the likely performance of a new districting plan for Wisconsin.

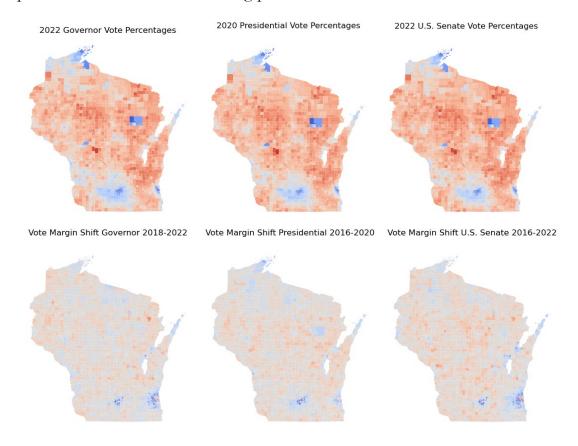


Figure 15: Comparison of vote percentage (top) to vote margin shift (bottom) for the 2018-2022 Governor elections, 2016-2020 Presidential elections, and 2016-2022 U.S. Senate elections.

Taking these observations together, I extend the analysis of partisan neutrality from above, by replacing the exogenous statewide elections with values from a regression model that incorporates more detailed information about the individual wards. Accounting for these issues allows us to best reflect likely outcomes in state-legislative elections in 2024 and 2026. As we will see, this analysis further demonstrates that the Wright Map attempts to treat voters from each party equally, according to the same standard symmetry metrics from political science introduced above.

To generate vote estimates I created two regression models, one for expected number of Republican legislative votes and one for expected number of Democratic legislative votes at the ward level. The regression models incorporate the same ward-level information as independent variables: voting age population, 2020 presidential vote counts for Biden, 2020 presidential vote counts for Trump, the vote margin shift from 2018 to 2022 in the Governor

race, county assignment, and incumbency, accounting for whether the likely incumbent had previously represented each ward in their new district. The 2022 assembly vote counts for each party in contested districts were used as the dependent variable for the model, as this was the election where the more refined version of incumbency could be estimated. I tested a wide variety of model variants using different regression approaches, all of which returned similar results, so this parsimonious model presents a good candidate for understanding likely partisanship in subsequent elections. I also validated this model against the 2020 and 2022 assembly elections under the previous map, where it correctly predicted the winner in 99/99 districts for 2022 and 98/99 districts for 2020, missing only Assembly District 73, where the actual election was decided by less than half a percentage point. Trained on a random 80% of the wards in contested districts, both models achieved R<sup>2</sup> values of over 90% on the test set consisting of the remaining 20% of wards. For the evaluation below, I trained the model on the contested elections for the corresponding year, although restricting to wards that had contested elections in each of the years under consideration did not significantly impact the model.

Thus, with a small number of covariates, I am able to make predictions for wards where there is not direct legislative voting data, since there are a significant number of uncontested seats in both houses during every election cycle. Using this model, I make ward-level estimates for legislative votes for both parties, compile wards into districts, and use this district-level vote data to compute the same partisan symmetry statistics as before with a uniform vote swing from the model to estimate a 50/50 election. Table 12 shows these values for the Wright Map, and the small magnitudes for each quantity demonstrate that this map treats voters from both parties symmetrically.

Wright	Mean	Partisan	Efficiency	Declination	Lopsided
Map	Median	Bias	Gap		Wins
Assembly	0.008	-0.005	0.003	0.016	-0.012
Senate	002	-0.045	-0.037	-0.070	-0.054

Table 12: Final partisan symmetry scores using the regression vote model for the Wright Map.

Figure 16 shows seats-votes curves for both houses of the Wright Map, and Figure 18 shows the same curves for the 2022 Map using this model. In a future statewide election that is tied, the 2022 Map would have resulted in a 27-seat Republican advantage in the Assembly and a 9-seat Republican advantage in the Senate, while the Wright Map would most likely result in a 52-47 Democratic majority in the Assembly and a 18-15 Republican majority in the Senate, both with several extremely competitive districts. As every seat in the Assembly is up

for election in 2024, this model demonstrates that under the Wright Map, the people of Wisconsin will be likely to achieve representation that reflects the majority will of the electorate. Under the Wright Map, most Democratic Senators and most Republican Senators already live in a new senate district with the same number as the district from which the Senator was most recently elected. In the Senate, only the 16 even-numbered districts will hold elections in 2024, and so it is useful to consider the expected partisan makeup of those districts under the election model. In this case, 10 out of the 16 districts have expected Democratic vote shares of at least 50%, and there are three districts, two Republican-leaning and one Democratic-leaning, with expected Democratic vote share within 0.5% of 50/50. While Republicans will retain their 12-5 advantage in the odd-numbered senate districts, this model predicts the possibility of majoritarian results for both parties if the overall vote share is nearly balanced.

Plotting the seats-votes curve for this model further supports the case that the Wright Map achieves a high degree of partisan symmetry. Figure 16 below shows the seats-votes curves for the model on both the assembly and senate districts, on the left and right, respectively. Unsurprisingly, as with Figure 10 above, both the Wright assembly map and the Wright senate map demonstrate strong symmetry properties.

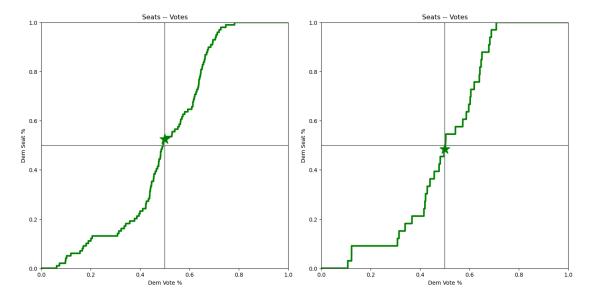


Figure 16: Seats-votes curves for the Wright Map under the regression vote model, with a vote swing to project a 50/50 election. For both the assembly map (left) and the senate map (right), the curves are very symmetric near 50/50.

To further apply the vote model, I simulated 1,000 draws at the ward level from the model for both the assembly and senate districts and computed the seats-votes curves for each sample. The 5<sup>th</sup> to 95<sup>th</sup> percentiles of these seats-votes

values are displayed in Figure 17 below, along with insets focusing on the region from 45% to 55% vote share. Impressively, for both the Wright assembly map and the Wright senate map, the confidence region includes the 50/50 point.

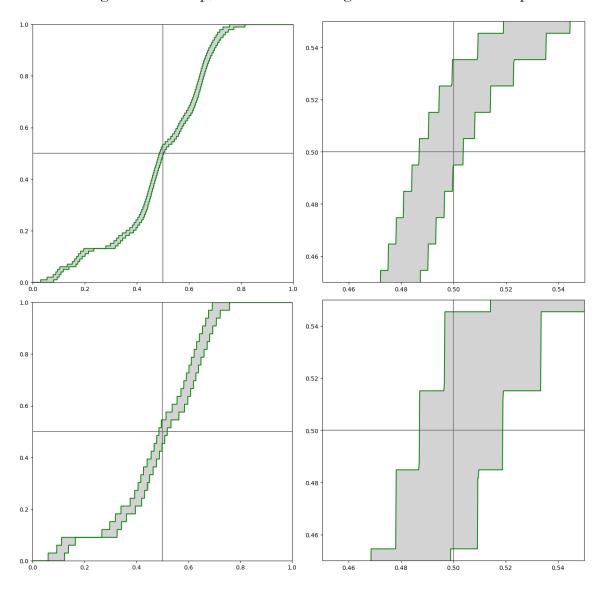


Figure 17: Seats-votes estimates for simulated elections drawn from the regression model for the Wright Map. Both the assembly map (top) and the senate map (bottom) contain the 50/50 point inside the 5th-95th percentiles of the samples.

To continue the comparison with the 2022 Map, I also predicted its performance under this model and constructed similar seats-votes curves and simulations. Those results are shown in Figure 18 below, demonstrating that the 2022 Map does not achieve partisan symmetry. Notice that the 5<sup>th</sup> to 95<sup>th</sup> percentiles of the simulations do not get close to the 50/50 points for either the 2022 assembly map or the 2022 senate map. This is further supported by the

partisan symmetry metrics evaluated on this map under the election model as shown in Table 13, which have large magnitudes and are all Republican-favoring.

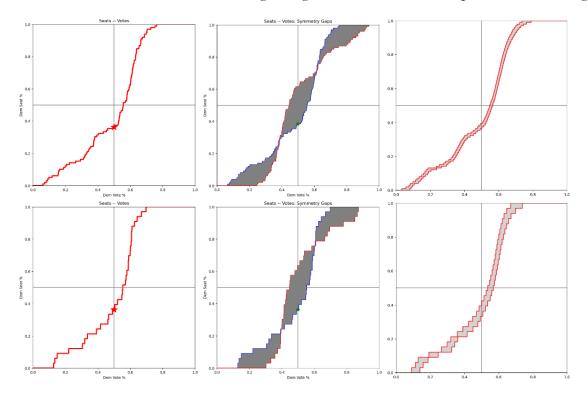


Figure 18: Seats-votes curves for the 2022 Map under the regression vote model. Note that both the Assembly (top) and the Senate (bottom) display characteristic asymmetry.

2022 Map	Mean Median	Partisan Bias	Efficiency Gap	Declination	Lopsided Wins
Assembly	-0.057	-0.146	-0.161	-0.347	-0.219
Senate	-0.070	-0.167	-0.157	-0.336	-0.200

Table 13: Partisan symmetry values for the 2022 assembly and senate maps under the election model.

#### VI.D Competitiveness and Responsiveness

In addition to direct measures of partisan symmetry the potential impact of a districting plan can also be evaluated by whether it is responsive to changes in the preferences of the electorate. Using the same statewide election information as above, we can create a simple measure of competitiveness and responsiveness by measuring how many safe districts there are for each party across the 19 elections considered. Table 14 shows the number of districts that were won by the same party in all or all but one of the 19 elections for the Wright Map. This demonstrates another sign of equal treatment, as there are the same

number of districts for each party that are consistently carried by statewide candidates for that party.

	Safe	Safe	Potentially
	Republican	Democratic	Responsive
Wright Assembly	40	40	19
Wright Senate	13	12	8

Table 14: Safe and potentially responsive districts over the 17 statewide general elections.

In addition, under my model, the Wright Map contains 15 assembly districts and 5 senate districts that are highly competitive, with both parties' candidates winning between 47% and 53% of the vote. And neither party has enough safe seats to guarantee control of either house, meaning control of each chamber will depend on winning competitive districts.

As another measure of responsiveness, we can compute the slope of a seats-votes curve near the 50/50 point. Fitting a linear curve to the points is reasonable in this case as the elections are clustered near 50/50, as shown in Figure 19. For both the Assembly and the Senate, the Wright Map has a slope between 2.0 and 2.5, which is consistent with a large body of political science literature for responsive plans.

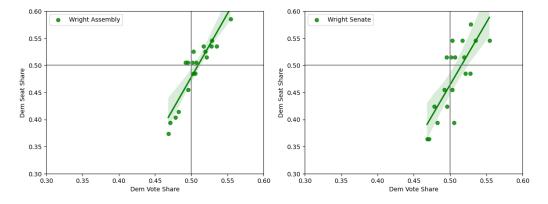


Figure 19: Linear seats-votes curves fit to the Wright Map evaluated with the 19 statewide elections. The slope is approximately 2.3 for both lines.

#### VI.E Ensembles and Sampling Methods

The ensemble method of evaluating districting plans consists of using computational sampling techniques to generate a large collection of comparison plans that satisfy some operationalization of the relevant state laws. The properties of these plans are often used to define a baseline or describe typical behavior of a plan that might be constructed without consideration of fairness

Ensemble methods are useful in determining when improper partisan gerrymandering has occurred. For example, in the case of a state that does not permit the use of partisan data in line drawing and does not have state constitutional protections for partisan neutrality, ensemble methods can show that it is highly unlikely that a plan was drawn without consideration of partisan data. Ensemble methods also can be used as a defense against poor performance on partisan symmetry metrics, for example by demonstrating that unintentional gerrymandering has generated an asymmetric map as a result of the underlying political geography. When, as here, the task is to determine appropriate target values for fairness metrics, these methods are less informative or dispositive.<sup>46</sup>

In many recent court cases, these types of ensemble methods have provided useful evidence of intent, demonstrating that a particular set of outcomes was very unlikely unless partisan data were used to inform the linedrawing process. Similarly, these methods have been used to justify maps with relatively large values on symmetry metrics, favoring one particular party, by demonstrating that such values are a likely consequence of the underlying geography. However, districting plans are not required to be constructed at random or to be randomly selected from those satisfying certain binary properties. Thus, a map whose scores lie closer to the center of such a distribution is not necessarily preferable to one that scores well on accepted measures of equal treatment of voters between the parties. Instead, the strong consensus in favor of the normative value of symmetry metrics among political scientists weighs towards selecting a plan that scores well on those metrics rather than one that happens to lie in the center of an ensemble. Otherwise, there is potential for both Type I and Type II errors in hewing too closely to ensemble methods.47

Taking all of this into account, an ensemble analysis that does not incorporate a partisan neutrality metric into its sampling distribution, either through a proposal method or by reweighting an observed sample, cannot be used to determine partisan neutrality as described by the court in its December 22 ruling. This would not be evaluating the relevant counterfactual and instead is simply reproducing the potential for unintentional gerrymandering due to the

<sup>&</sup>lt;sup>46</sup> See J. Chen and J. Rodden, Unintentional Gerrymandering: Political Geography and Electoral Bias in Legislatures, 8 Q. J. OF POL. SCI. 239–69 (2013).

<sup>&</sup>lt;sup>47</sup> See B. Grofman, Preliminary Report: Proposed Legislative and Congressional Remedial Plans in North Carolina (2022).

political geography of the state. Thus, a baseline that does not incorporate partisan neutrality is not likely to help distinguish between plans that satisfy the constitutional criteria. Instead, the approach taken in Section VI above that focuses on measures of partisan neutrality that are designed and understood to be normatively desirable, such as symmetry and responsiveness, should be preferred for this application.

With respect to Wisconsin's political geography, both previous ensemble analysis<sup>48</sup> as well as ensembles from this cycle<sup>49</sup> demonstrate that ensemble samples drawn without specific attention to partisan neutrality are not symmetric for near-50/50 elections. This does not mean that a plan must be similarly asymmetric to be neutral, but rather that neutrality as a desirable aim does not come just from randomly generating plans that ignore neutrality. By scoring well on established measures of partisan neutrality as detailed in Section VI above, the Wright Map treats voters more equitably and neutrally with respect to their party affiliation than would a random sample of maps.

### VII Summary and Conclusions

For the reasons outlined above, the Wright Map submitted by the Wright Petitioners satisfies all mandatory state and federal districting requirements, and excels on traditional districting criteria, while also achieving political neutrality significantly beyond that achieved by the 2022 Map.

<sup>&</sup>lt;sup>48</sup> See, e.g., G. Herschlag, R. Ravier, and J. Mattingly, Evaluating Partisan Gerrymandering in Wisconsin, ARXIV: 1709:01596 (2017).

<sup>&</sup>lt;sup>49</sup> For example, see the Princeton Election Project's Redistricting Report Card, which uses an ensemble analysis baseline, available at https://gerrymander.princeton.edu/redistricting-report-card, or the ALARM redistricting data published in C. McCartan, C. Kenny, T. Simko, G. Garcia III, K. Wang, M. Wu, S. Kuriwaki, and K. Imai, 9 *Simulated Redistricting Plans for the Analysis and Evaluation of Redistricting in the United States*, SCI. DATA 1 (2022).

I affirm that the above analysis reflects my assessment of the Wright Map.

47

### Appendix A: Other Data and Inputs

In addition to the data agreed to by the parties by stipulation, I used the following data:

- Vote totals from the Wisconsin LTSB were prorated onto census blocks by voting-age population and then reaggregated onto corrected wards. These are provided on the WIvotes shapefile uploaded with the replication materials. I also labeled each legislative election with its status as a contested election and whether there was an incumbent running in the same shapefile.
- To perform the COI analysis I used a block assignment file containing the following columns:
  - Media Markets
  - School Districts
  - o NAMELSAD20
  - The 36 cores of the People's Maps Commission COIs
- Addresses for current incumbents, as agreed to by the parties. To avoid revealing any confidential home addresses of incumbents, I associated these addresses with corrected wards and use those assignments for determining the incumbency variables in the regression model. This mapping of incumbents to wards, as well as a separate file for the 2022 Map specifically, is included in the replication materials.
- From the census block shapefile I created a dual graph that is included with the replication materials.
- Block assignment files for the 2022 senate and assembly plans included with the replication materials
- The regression model that I trained is saved as a pair of .pkl files included with the replication materials

### Appendix B: Replication Code

Python scripts to replicate the analysis above are provided in the Wright\_Replication.zip directory. The exception to this is values reported from external sources such as Dave's Redistricting App and PlanScore, which are noted in the Appendix below. In addition to reproducing the analysis in this report, the included script will allow similar results to be reported for any other map submitted as a block assignment file. The code is contained in the Compare\_Maps.ipynb notebook. To evaluate another plan on exactly the same set of metrics that I applied to the Wright Map, the data input in the second code cell needs to be adjusted as follows:

- Num\_plans is the number of maps to be compared at once. If set to 1 this will just report the values for a single plan.
- Plan\_names should be a list of string titles for the plans, primarily used for labelling in visualizations and tables, with length equal to Num\_plans.
- Plan\_locations should be a list of file references to the .csv files containing the block assignments for each plan, ordered to align with the entries in Plan\_names.
- Plan\_columns should provide the name of the column containing the district label for each block or the string "None" if no header is provided in the .csv, ordered to align with the entries in Plan\_names.
- Block\_columns should provide the name of the column containing the BLOCKIDs in the block assignment file.

For example, setting the following lines in that file will produce a comparison between the Wright Map and the 2022 Map:

- $num_plans = 2$
- plan\_names = ["Wright","2022"]
- plan\_locations = [("./Plans/Wright\_ASM.csv","./Plans/Wright\_SEN.csv"),("./Plans/202
   2\_ASM.csv","./Plans/2022\_SEN.csv")]
- block\_columns = [("BLOCKID","BLOCKID"),("BLOCKID","BLOCKID")]
- plan\_columns = [("assem\_dist","sen\_dist"),("ASM\_22","SEN\_22")]

This notebook should take approximately 45 minutes to run in its entirety for a pair of maps and it will create the relevant plots and visualizations inline throughout the notebook cells.

# Appendix C: District Metric Values

## C.1 Population Equality Assembly

AD		Population
	1	59444
	2	59973
	3	59306
	4	59258
	5	58989
	6	60024
	7	59603
	8	59362
	9	59571
	10	59503
	11	59565
	12	59351
	13	60008
	14	59960
	15	59713
	16	59714
	17	59435
	18	59346
	19	59320
	20	59548

21	59592
22	59105
23	59274
24	59171
25	59165
26	59860
27	59412
28	59467
29	59623
30	59148
31	59562
32	59797
33	60077
34	59589
35	59756
36	59001
37	59866
38	60017
39	59423
40	59349
41	59358
42	59631
43	59935
44	59911

45	59100
46	59569
47	59898
48	59177
49	59218
50	59061
51	59498
52	60050
53	59040
54	59545
55	59407
56	59129
57	59603
58	59161
59	59554
60	59922
61	59883
62	60001
63	59475
64	59732
65	59821
66	59904
67	59340
68	59375

69	59460
70	59027
71	59999
72	59139
73	59097
74	59253
75	59520
76	59412
77	59722
78	59918
79	59850
80	59713
81	59167
82	58988
83	60051
84	60046
85	59116
86	59927
87	59383
88	59919
89	59059
90	59109
91	59434
92	59384

94	60052
95	60057
96	58992
97	59559

# C.2 Population Equality Senate

SEN	Population
1	178723
2	178271
3	178536
4	178419
5	179681
6	178495
7	178460
8	177550
9	178437
10	178238
11	179436
12	178346
13	179306
14	178338
15	178946
16	178644
17	177777
18	178635
19	178139

- 20 178637
- 21 179359
- 22 179457
- 23 178175
- 24 178165
- 25 177870
- 26 179052
- 27 178730
- 28 179085
- 29 178426
- 30 178087
- 31 178360
- 32 179101
- 33 178837

# C.3 County Splits Assembly

CNTY NAME	
Adams	[49, 81, 50]
Barron	[73, 75, 67, 30]
Bayfield	[36, 74]
Brown	[89, 88, 90, 5, 1, 3, 6]
Calumet	[60, 27, 3]
Chippewa	[67, 91, 93]
Clark	[67, 69]
Columbia	[79, 81, 42, 40, 39, 80]
	, 48, 40, 42, 41, 94, 79, 47, 76, 78]
Dodge	[97, 39, 40, 53, 37]
Dunn	[30, 92, 68, 93]
Eau Claire	[93, 91, 92]
Fond du Lac	[55, 39, 26, 52, 27, 53]
Green	[48, 46, 45]
Iowa	[95, 96]
Jackson	[69, 68]
Jefferson	[41, 43, 99, 97, 40]
Juneau	[50, 80, 81]
Kenosha	[31, 32, 64, 65] [70, 72, 71]
La Crosse	[48, 96, 95]
Lafayette Manitowoc	[40, 90, 95]
Marathon	[67, 86, 51, 85, 35, 57, 69]
Milwaukee	[23, 12, 20, 82, 21, 10, 84,
MILLWAUNCC	
7 - 61 - 11 - 17 - 18 - 16 - 19 -	
7, 61, 11, 17, 18, 16, 19, Monroe	9, 8, 14, 15]
Monroe	9, 8, 14, 15] [50, 70]
Monroe Oconto	9, 8, 14, 15] [50, 70] [6, 4, 34, 57]
Monroe Oconto Oneida	9, 8, 14, 15] [50, 70] [6, 4, 34, 57] [36, 34]
Monroe Oconto	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]
Monroe Oconto Oneida Outagamie	9, 8, 14, 15] [50, 70] [6, 4, 34, 57] [36, 34]
Monroe Oconto Oneida Outagamie Ozaukee	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]
Monroe Oconto Oneida Outagamie Ozaukee Pierce	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]  [30, 29]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]  [30, 29]  [28, 73]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]  [30, 29]  [28, 73]  [87, 49, 51]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]  [30, 29]  [28, 73]  [87, 49, 51]  [63, 82, 66, 83, 64, 31]  [45, 33, 32, 43, 46, 44]  [81, 95, 80]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]  [30, 29]  [28, 73]  [87, 49, 51]  [63, 82, 66, 83, 64, 31]  [45, 33, 32, 43, 46, 44]  [81, 95, 80]  [57, 6]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano Sheboygan	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]  [30, 29]  [28, 73]  [87, 49, 51]  [63, 82, 66, 83, 64, 31]  [45, 33, 32, 43, 46, 44]  [81, 95, 80]  [57, 6]  [26, 27, 25]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]  [30, 29]  [28, 73]  [87, 49, 51]  [63, 82, 66, 83, 64, 31]  [45, 33, 32, 43, 46, 44]  [81, 95, 80]  [57, 6]  [26, 27, 25]  [30, 28, 29]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano Sheboygan St. Croix Taylor	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]  [30, 29]  [28, 73]  [87, 49, 51]  [63, 82, 66, 83, 64, 31]  [45, 33, 32, 43, 46, 44]  [81, 95, 80]  [57, 6]  [26, 27, 25]  [30, 28, 29]  [67, 35]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano Sheboygan St. Croix Taylor Vernon	9, 8, 14, 15]  [50, 70] [6, 4, 34, 57] [36, 34] [60, 59, 56, 58, 3, 5] [23, 38, 24] [30, 29] [28, 73] [87, 49, 51] [63, 82, 66, 83, 64, 31] [45, 33, 32, 43, 46, 44] [81, 95, 80] [57, 6] [26, 27, 25] [30, 28, 29] [67, 35] [71, 50, 95]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano Sheboygan St. Croix Taylor Vernon Walworth	9, 8, 14, 15]  [50, 70] [6, 4, 34, 57] [36, 34] [60, 59, 56, 58, 3, 5] [23, 38, 24] [30, 29] [28, 73] [87, 49, 51] [63, 82, 66, 83, 64, 31] [45, 33, 32, 43, 46, 44] [81, 95, 80] [57, 6] [26, 27, 25] [30, 28, 29] [67, 35] [71, 50, 95] [32, 63, 33, 99, 44, 43]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano Sheboygan St. Croix Taylor Vernon Walworth Washington	9, 8, 14, 15]  [50, 70] [6, 4, 34, 57] [36, 34] [60, 59, 56, 58, 3, 5] [23, 38, 24] [30, 29] [28, 73] [87, 49, 51] [63, 82, 66, 83, 64, 31] [45, 33, 32, 43, 46, 44] [81, 95, 80] [57, 6] [26, 27, 25] [30, 28, 29] [67, 35] [71, 50, 95] [32, 63, 33, 99, 44, 43] [37, 38, 97, 22, 26, 39]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano Sheboygan St. Croix Taylor Vernon Walworth Washington Waukesha	9, 8, 14, 15]  [50, 70]  [6, 4, 34, 57]  [36, 34]  [60, 59, 56, 58, 3, 5]  [23, 38, 24]  [30, 29]  [28, 73]  [87, 49, 51]  [63, 82, 66, 83, 64, 31]  [45, 33, 32, 43, 46, 44]  [81, 95, 80]  [57, 6]  [26, 27, 25]  [30, 28, 29]  [67, 35]  [71, 50, 95]  [32, 63, 33, 99, 44, 43]  [37, 38, 97, 22, 26, 39]  [62, 14, 15, 13, 97, 99, 98, 22, 61]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano Sheboygan St. Croix Taylor Vernon Walworth Washington Waukesha Waupaca	9, 8, 14, 15]  [50, 70] [6, 4, 34, 57] [36, 34] [60, 59, 56, 58, 3, 5] [23, 38, 24] [30, 29] [28, 73] [87, 49, 51] [63, 82, 66, 83, 64, 31] [45, 33, 32, 43, 46, 44] [81, 95, 80] [57, 6] [26, 27, 25] [30, 28, 29] [67, 35] [71, 50, 95] [32, 63, 33, 99, 44, 43] [37, 38, 97, 22, 26, 39] [62, 14, 15, 13, 97, 99, 98, 22, 61] [57, 56]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano Sheboygan St. Croix Taylor Vernon Walworth Washington Waukesha Waupaca Waushara	9, 8, 14, 15]  [50, 70] [6, 4, 34, 57] [36, 34] [60, 59, 56, 58, 3, 5] [23, 38, 24] [30, 29] [28, 73] [87, 49, 51] [63, 82, 66, 83, 64, 31] [45, 33, 32, 43, 46, 44] [81, 95, 80] [57, 6] [26, 27, 25] [30, 28, 29] [67, 35] [71, 50, 95] [32, 63, 33, 99, 44, 43] [37, 38, 97, 22, 26, 39] [62, 14, 15, 13, 97, 99, 98, 22, 61] [57, 56] [57, 56]
Monroe Oconto Oneida Outagamie Ozaukee Pierce Polk Portage Racine Rock Sauk Shawano Sheboygan St. Croix Taylor Vernon Walworth Washington Waukesha Waupaca	9, 8, 14, 15]  [50, 70] [6, 4, 34, 57] [36, 34] [60, 59, 56, 58, 3, 5] [23, 38, 24] [30, 29] [28, 73] [87, 49, 51] [63, 82, 66, 83, 64, 31] [45, 33, 32, 43, 46, 44] [81, 95, 80] [57, 6] [26, 27, 25] [30, 28, 29] [67, 35] [71, 50, 95] [32, 63, 33, 99, 44, 43] [37, 38, 97, 22, 26, 39] [62, 14, 15, 13, 97, 99, 98, 22, 61] [57, 56]

# C.4 County Splits Senate

CNTY NAME		
Adams	[17, 27	1
Barron	[25, 23, 10	_
Bayfield	[12, 25	
Brown	[30, 2, 1	
Calumet	[20, 9, 1	.]
Chippewa	[23, 31	
Columbia	[27, 14, 13	; ]
Dane	[15, 16, 27, 32, 26, 14	.]
Dodge	[33, 13, 14, 18	; ]
Dunn	[10, 31, 23	
Fond du Lac	[19, 13, 9, 18	
Green	[16, 15	
Jefferson	[14, 15, 33	;]
Juneau	[17, 27	]
Kenosha	[11, 22	:]
Lafayette	[16, 32	:]
Manitowoc	[9, 1	. ]
Marathon	[23, 29, 17, 12, 19	)]
Milwaukee	[8, 4, 7, 28, 3, 21, 6, 5	
Monroe	[17, 24	: ]
Oconto	[2, 12, 19	
Outagamie	[20, 19, 1, 2	
Ozaukee	[8, 13	
Polk	[10, 25	
Portage	[29, 17	
Racine	[21, 28, 22, 11	
Rock	[15, 11, 16	
Sauk	[27, 32	
Shawano	[19, 2	
Taylor	[23, 12	
Vernon	[24, 17, 32	. ]
Walworth	[11, 21, 33, 15	) ]
Washington	[13, 33, 8, 9	, ]
Waukesha	[21, 5, 33, 8	]
Waushara	[19, 17	]
Winnebago	[18, 20, 19	
Wood	[17, 23	, ]
Name: sen dist.	. dtype: object	

### Name: sen\_dist, dtype: object

## C.5 Town Splits Assembly

01025	[53,	54]
10050	[13,	15]
10750	[3,	60]
26300	[52 <b>,</b>	53]
37925	[41,	43]
42900	[3,	5]
48025	[47, 76,	94]
50400	[70,	72]
51400	[97,	98]

51600	[78, 80,	94]
55075	[62,	99]
73000	[25,	26]
73125	[70,	71]
82625	[48,	94]
84275	[13,	62]

## C.6 Town Splits Senate

10750	[1, 20]
37925	[14, 15]
42900	[1, 2]
48025	[16, 26, 32]
51600	[26, 27, 32]
55075	[21, 33]
82625	[16, 32]
84275	[5, 21]

## **C.7** Compactness Assembly

AD		PolsbyPopper	Convex Hull	Reock
	1	0.092379	0.549934	0.148452
	2	0.54125	0.902779	0.418565
	3	0.33946	0.776007	0.396052
	4	0.326474	0.744511	0.512814
	5	0.358848	0.819795	0.469126
	6	0.364005	0.834219	0.546756
	7	0.13645	0.525179	0.188434
	8	0.358454	0.81249	0.469129
	9	0.230016	0.667422	0.357359

10	0.154729	0.590565	0.341807
11	0.246169	0.731116	0.431028
12	0.332744	0.813637	0.388712
13	0.137731	0.642815	0.421579
14	0.285308	0.725876	0.445257
15	0.21343	0.573767	0.2526
16	0.347929	0.740898	0.422783
17	0.329805	0.744254	0.421079
18	0.212386	0.567735	0.273496
19	0.119543	0.487401	0.187604
20	0.396438	0.76894	0.536433
21	0.367496	0.820868	0.41078
22	0.603153	0.978503	0.497012
23	0.23275	0.685837	0.281458
24	0.277401	0.688303	0.341907
25	0.314519	0.787271	0.35364
26	0.381479	0.813122	0.513106
27	0.369822	0.725715	0.454864
28	0.553836	0.858131	0.611776
29	0.300976	0.739576	0.422211
30	0.258348	0.716247	0.415826
31	0.245377	0.703791	0.405367
32	0.292181	0.68833	0.323655
33	0.26173	0.663096	0.328431

34	0.36926	0.785638	0.558099
35	0.36029	0.734936	0.461658
36	0.15073	0.523376	0.316954
37	0.45276	0.739944	0.471134
38	0.448659	0.880903	0.392048
39	0.331086	0.715615	0.432672
40	0.412737	0.787572	0.442647
41	0.403288	0.799216	0.405708
42	0.317639	0.821172	0.336695
43	0.251275	0.69446	0.383084
44	0.329311	0.713075	0.440365
45	0.41597	0.705246	0.432323
46	0.351775	0.742926	0.497996
47	0.252824	0.718544	0.449728
48	0.295771	0.706932	0.396848
49	0.458537	0.824962	0.636752
50	0.24143	0.647381	0.464813
51	0.259947	0.743144	0.464744
52	0.378661	0.796512	0.396939
53	0.33257	0.894551	0.386683
54	0.224867	0.758902	0.490004
55	0.297517	0.698667	0.309016
56	0.35367	0.716149	0.407432
57	0.443631	0.825264	0.406317

58	0.33009	0.810094	0.316804
59	0.508555	0.903179	0.486524
60	0.393841	0.825954	0.594025
61	0.470379	0.80286	0.497395
62	0.208229	0.713239	0.394305
63	0.319682	0.710296	0.30522
64	0.264482	0.736578	0.495372
65	0.127971	0.740104	0.551187
66	0.23465	0.67528	0.45466
67	0.331153	0.776967	0.454223
68	0.392869	0.804651	0.467451
69	0.395743	0.81655	0.508966
70	0.296991	0.703605	0.518218
71	0.424275	0.821591	0.451518
72	0.29289	0.778815	0.46513
73	0.55941	0.880933	0.569769
74	0.305547	0.81293	0.421677
75	0.46681	0.824525	0.55721
76	0.213558	0.514358	0.243028
77	0.264084	0.819134	0.596084
78	0.255706	0.721923	0.394332
79	0.292242	0.730396	0.366317
80	0.158093	0.641874	0.248065
81	0.332258	0.708744	0.412437

82	0.188606	0.619326	0.320824
83	0.246975	0.685722	0.288613
84	0.214149	0.674375	0.38994
85	0.336383	0.799073	0.441699
86	0.28441	0.74005	0.417547
87	0.427061	0.815621	0.530818
88	0.263399	0.791442	0.433433
89	0.207428	0.642006	0.282571
90	0.160495	0.65398	0.47978
91	0.276877	0.818078	0.359356
92	0.308239	0.706927	0.451556
93	0.410272	0.825977	0.392309
94	0.125917	0.659957	0.27131
95	0.369864	0.768637	0.420165
96	0.466694	0.848883	0.606727
97	0.295183	0.806111	0.421588
98	0.276238	0.804688	0.556329
99	0.25224	0.768427	0.424225

## C.8 Compactness Senate

SEN		PolsbyPopper	Convex Hull	Reock
	1	0.078927	0.471787	0.15498
	2	0.23977	0.741676	0.383081
	3	0.296593	0.786933	0.417319

4	0.227491	0.707748	0.379696
5	0.134381	0.627979	0.35549
6	0.242011	0.714527	0.515872
7	0.180423	0.631246	0.241631
8	0.19653	0.622902	0.286992
9	0.368899	0.797668	0.479992
10	0.498992	0.826914	0.581023
11	0.207644	0.757276	0.240113
12	0.195532	0.661071	0.407963
13	0.26886	0.743312	0.328204
14	0.327864	0.827509	0.44582
15	0.258233	0.761803	0.409394
16	0.263292	0.788335	0.378335
17	0.245534	0.731557	0.496361
18	0.245249	0.724196	0.50045
19	0.246185	0.745343	0.328761
20	0.249303	0.715887	0.39002
21	0.220914	0.63921	0.473946
22	0.206857	0.822398	0.455474
23	0.203253	0.691846	0.501442
24	0.310098	0.744604	0.347327
25	0.326348	0.805547	0.50573
26	0.18742	0.734714	0.386482
27	0.336672	0.819994	0.392721

28	0.143956	0.565646	0.223189
29	0.416898	0.821107	0.496399
30	0.224508	0.709769	0.423676
31	0.324456	0.784389	0.422361
32	0.277385	0.742666	0.501106
33	0.266339	0.714637	0.491731

### Appendix D: Third Party Web Applications

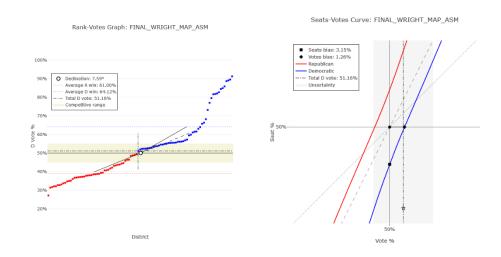
In this section, I report the values observed in two popular web applications for analyzing redistricting plans when applied to the Wright Map. These applications have their own data processing and vote modeling standards and have become widely used throughout the country for generating reports and information about proposed maps. The specific values that are reported do not agree exactly with the calculations I present in my report. As an example, Dave's Redistricting App gives the Wright Map larger values of the Polsby-Popper metric than I do as a result of some of its underlying data processing choices. Even so, all of this information remains supportive of the main points of my report that the Wright Map is constitutional and significantly outperforms the 2022 Map with regard to partisan neutrality.

For the statistics from Dave's Redistricting App, I report values that correspond to uploading block assignment files for the Wright Map, using the "Wisconsin Wards with Dec 2023 LTSB Corrections" precincts update and the 2016-2022 composite election data. For PlanScore, I uploaded shapefiles of the Wright maps and used the "New: rerun the 2020 election with more accurate updated data (updated May 2022)" option for vote analysis, as well as inputting the incumbent matchings to districts that correspond to the ones used to train and evaluate my vote model above.

All of the following tables, values, and plots are taken directly from the corresponding app. Additional outputs from these apps are included in the data provided to the Court and its consultants.

### D.1 Dave's Redistricting App Assembly

## (Partisan) Bias Measures and Responsiveness Measures



Proportional	1.39%
Efficiency gap	2.55%
Gamma	2.96%
Seats bias	3.15%
Votes bias	1.26%
Partisan bias	3.33%
Global symmetry	3.04%
Partisan bias rating	67
Declination	7.59°
Mean-median	0.03%
Turnout bias	-0.78%
Lopsided outcomes	3.99%
Proportional seats	50.65
Geographic seats	42.71
Geographic bias	8.02%
Map seats	49.28
Boundary bias	-6.63%
Responsiveness	2.36
Responsive districts	20.69
Overall responsiveness	-0.20

## Compactness

ID	Reock	Rating	Polsby- Popper	Rating	KIWYSI Score
1	0.1561	0	0.1132	3	6
2	0.4824	93	0.5771	100	91
3	0.3269	31	0.3103	53	55
4	0.5416	100	0.3333	58	56
5	0.5701	100	0.3627	66	67
6	0.4526	81	0.3618	65	70
7	0.1822	0	0.1364	9	8
8	0.5885	100	0.3623	66	67
9	0.4328	73	0.235	34	36
10	0.3775	51	0.1621	16	22
11	0.3803	52	0.2403	35	44
12	0.4844	94	0.3411	60	61
13	0.3222	29	0.14	10	23
14	0.3437	37	0.2727	43	46
15	0.2245	0	0.1999	25	20
16	0.4728	89	0.3586	65	57
17	0.3518	41	0.3222	56	53
18	0.2679	7	0.2115	28	21
19	0.2472	0	0.1388	10	9
20	0.4323	73	0.392	73	63
21	0.3401	36	0.344	61	65
22	0.5751	100	0.6605	100	100
23	0.2766	11	0.2354	34	34
24	0.3363	35	0.2876	47	40
25	0.4539	82	0.368	67	63
26	0.4564	83	0.3707	68	69
27	0.4126	65	0.3712	68	57
28	0.513	100	0.5226	100	91
29	0.448	79	0.2959	49	50
30	0.335	34	0.2466	37	40
31	0.3165	27	0.2364	34	38
32	0.2473	0	0.261	40	42
33	0.2541	2	0.2389	35	38
34	0.4532	81	0.3581	65	61
35	0.4444	78	0.3551	64	56
36	0.2744	10	0.1447	11	12
37	0.3819	53	0.4239	81	66
38	0.3138	26	0.4034	76	79
39	0.33	32	0.3129	53	50
40	0.3487	39	0.3861	72	66
41	0.323	29	0.3635	66	66
42	0.4105	64	0.3391	60	57
43	0.2899	16	0.2399	35	41

44	0.3575	43	0.3123	53	50
45	0.4031	61	0.4051	76	59
46	0.5009	100	0.3561	64	57
47	0.3589	44	0.2583	40	42
48	0.3413	37	0.2776	44	45
49	0.5117	100	0.4393	85	76
50	0.4027	61	0.2337	33	35
51	0.4585	83	0.2517	38	47
52	0.3767	51	0.3914	73	64
53	0.4829	93	0.402	75	74
54	0.44	76	0.241	35	48
55	0.2962	18	0.2887	47	41
56	0.3429	37	0.3366	59	51
57	0.4529	81	0.4509	88	73
58	0.343	37	0.3627	66	56
59	0.4257	70	0.4908	98	89
60	0.4416	77	0.3827	71	70
61	0.5291	100	0.4768	94	77
62	0.3404	36	0.2067	27	36
63	0.2274	0	0.2839	46	46
64	0.5298	100	0.2809	45	50
65	0.4609	84	0.1368	9	36
66	0.3749	50	0.2268	32	37
67	0.3537	41	0.3077	52	58
68	0.3533	41	0.3677	67	64
69	0.4799	92	0.3859	71	70
70	0.4639	86	0.2892	47	46
71	0.5051	100	0.4304	83	71
72	0.5262	100	0.2955	49	56
73	0.4701	88	0.5337	100	91
74	0.3635	45	0.2991	50	56
75	0.503	100	0.4657	91	77
76	0.2363	0	0.2276	32	18
77	0.4844	94	0.2657	41	57
78	0.3224	29	0.2521	38	43
79	0.4583	83	0.3065	52	50
80	0.2509	0	0.1566	14	20
81	0.3153	26	0.3077	52	50
82	0.2972	19	0.1824	21	24
83	0.3658	46	0.2633	41	38
84	0.3374	35	0.2096	27	34
85	0.3691	48	0.3159	54	57
86	0.342	37	0.2768	44	49
87	0.4551	82	0.388	72	74
88	0.3503	40	0.2435	36	49

89	0.268	7	0.2057	26	28
90	0.4717	89	0.1583	15	30
91	0.2614	5	0.2564	39	55
92	0.3897	56	0.3019	50	47
93	0.3058	22	0.375	69	67
94	0.2038	0	0.1185	5	21
95	0.4327	73	0.37	68	59
96	0.5011	100	0.4556	89	79
97	0.3228	29	0.2742	44	54
98	0.5332	100	0.2967	49	57
99	0.4413	77	0.2558	39	49

### **Splitting**

In this map, 47 counties are split a total of 153 times: Adams (2), Barron (3), Bayfield (1), Brown (6), Calumet (2), Chippewa (2), Clark (1), Columbia (5), Dane (13), Dodge (4), Dunn (3), Eau Claire (2), Fond du Lac (5), Green (2), Iowa (1), Jackson (1), Jefferson (4), Juneau (2), Kenosha (3), La Crosse (2), Lafayette (2), Manitowoc (2), Marathon (6), Milwaukee (17), Monroe (1), Oconto (3), Oneida (1), Outagamie (5), Ozaukee (2), Pierce (1), Polk (1), Portage (2), Racine (5), Rock (5), Sauk (2), Shawano (1), Sheboygan (2), St. Croix (2), Taylor (1), Vernon (2), Walworth (5), Washington (5), Waukesha (8), Waupaca (1), Waushara (1), Winnebago (4), and Wood (2).

Twenty five counties -- Racine, Rock, St. Croix, Sauk, Sheboygan, Walworth, Washington, Waukesha, Winnebago, Wood, Brown, Chippewa, Dane, Dodge, Eau Claire, Fond du Lac, Jefferson, Kenosha, La Crosse, Manitowoc, Marathon, Milwaukee, Outagamie, Ozaukee, and Portage -- may have to be split, because they have more people than a district. The resulting splits could yield 65 single-county districts. There are 37.

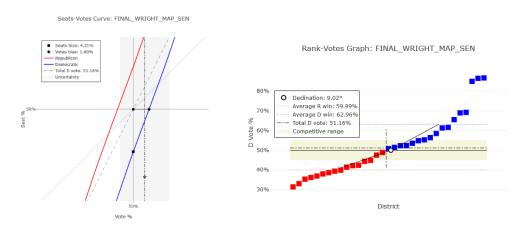
Altogether, these splits affect 41.43% of people in the state.

To achieve almost exactly equal district populations, 98 precincts may also have to be split, and zero are.

Fifty two of 1,850 cities are split: Algoma town, Appleton, Ashwaubenon, Brookfield city, Brookfield town, Brown Deer, Buchanan, Caledonia village, DeForest, Eau Claire, Elkhorn, Fond du Lac town, Fox Crossing, Franklin city, Green Bay city, Greendale, Greenfield city, Harrison village, Howard village, Janesville city, Jefferson town, Kenosha, La Crosse, Lawrence town, Madison city, Madison town, McFarland, Medary, Menasha, Menomonee Falls, Mequon, Merton town, Middleton town, Milwaukee, Mount Pleasant village, Mukwonago town, Mukwonago village, Muskego, Oshkosh city, Racine, Raymond, Saukville village, Sheboygan town, Shelby, Sun Prairie city, Verona city, Verona town, Watertown city, Waukesha city, Waukesha town, Wauwatosa, and West Allis.

# D.2 Dave's Redistricting App Senate

# (Partisan) Bias Measures and Responsiveness Measures



Proportional	2.35%
Efficiency gap	3.51%
Gamma	4.27%
Seats bias	4.31%
Votes bias	1.60%
Partisan bias	4.40%
Global symmetry	2.75%
Partisan bias rating	59
Declination	9.02°
Mean-median	1.01%
Turnout bias	-0.67%
Lopsided outcomes	4.20%
Proportional seats	16.88
Geographic seats	14.24
Geographic bias	8.02%
Map seats	16.11
Boundary bias	-5.67%
Responsiveness	2.65
Responsive districts	7.68
Overall responsiveness	-1.02

# Compactness

ID	Reock	Rating	Polsby- Popper	Rating	KIWYSI Score
1	0.1503	0	0.0905	0	1
2	0.5354	100	0.2474	37	47
3	0.3888	56	0.2888	47	52
4	0.3373	35	0.2310	33	38
5	0.2649	6	0.1312	8	21
6	0.3978	59	0.2314	33	42
7	0.2777	11	0.1905	23	24
8	0.2951	18	0.2103	28	26
9	0.5241	100	0.3865	72	67
10	0.5529	100	0.4859	96	82
11	0.1808	0	0.1879	22	41
12	0.3667	47	0.1890	22	29
13	0.2403	0	0.2479	37	44
14	0.4603	84	0.3240	56	63
15	0.3739	50	0.2447	36	48
16	0.3040	22	0.2511	38	48
17	0.3857	54	0.2377	34	43
18	0.4734	89	0.2817	45	48
19	0.4120	65	0.2440	36	45
20	0.4090	64	0.2513	38	42
21	0.3570	43	0.2156	29	32
22	0.5743	100	0.2251	31	53
23	0.4073	63	0.1918	23	36
24	0.4580	83	0.3135	53	54
25	0.4701	88	0.3314	58	60
26	0.2934	17	0.1840	21	38
27	0.3725	49	0.3368	59	60
28	0.2468	0	0.1433	11	13
29	0.4739	90	0.4051	76	71
30	0.4107	64	0.2173	29	39
31	0.3155	26	0.3083	52	55
32	0.3682	47	0.2700	43	46
33	0.4796	92	0.2638	41	47

### **Splitting**

In this map, 37 counties are split a total of 74 times: Adams (1), Barron (2), Bayfield (1), Brown (2), Calumet (2), Chippewa (1), Columbia (2), Dane (5), Dodge (3), Dunn (2), Fond du Lac (3), Green (1), Jefferson (2), Juneau (1), Kenosha (1), Lafayette (1), Manitowoc (1), Marathon (4), Milwaukee (7), Monroe (1), Oconto (2), Outagamie (3), Ozaukee (1), Polk (1), Portage (1), Racine (3), Rock (2), Sauk (1), Shawano (1), Taylor (1), Vernon (2), Walworth (3), Washington (3), Waukesha (3), Waushara (1), Winnebago (2), and Wood (1).

Six counties -- Racine, Waukesha, Brown, Dane, Milwaukee, and Outagamie -- may have to be split, because they have more people than a district. The resulting splits could yield 13 single-county districts. There are six.

Altogether, these splits affect 58.22% of people in the state.

To achieve almost exactly equal district populations, 32 precincts may also have to be split, and zero are.

Thirty four of 1,850 cities are split: Appleton, Ashwaubenon, Brown Deer, Buchanan, Caledonia village, DeForest, Fox Crossing, Franklin city, Green Bay city, Greenfield city, Harrison village, Howard village, Janesville city, Jefferson town, Kenosha, Lawrence town, Madison city, Madison town, McFarland, Menasha, Menomonee Falls, Middleton town, Milwaukee, Mukwonago town, Racine, Raymond, Saukville village, Verona city, Verona town, Watertown city, Waukesha city, Waukesha town, Wauwatosa, and West Allis.

The overall city-district splitting rating is 35.

# D.3 PlanScore Assembly

# Partisan Symmetry Measures

Metric	Value	Favors
Efficiency Gap	5.9%	Pro-Republican
Declination	0.32	Pro-Republican
Partisan Bias	5.1%	Pro-Republican
Mean-Median	2.1%	Pro-Republican

# Inefficiency in Freedom to Vote Act Races

Contest	Value	Favors
President 2020	1.9%	Pro-Democratic
President 2016	3.7%	Pro-Republican
Senate 2018	2.3%	Pro-Republican
Senate 2016	5.1%	Pro-Republican

## D.4 PlanScore Senate

# Partisan Symmetry Measures

Metric	Value	Favors
Efficiency Gap	7.4%	Pro-Republican
Declination	0.29	Pro-Republican
Partisan Bias	6.5%	Pro-Republican
Mean-Median	2.6%	Pro-Republican

# Inefficiency in Freedom to Vote Act Races

Contest	Value	Favors
President 2020	3.9%	Pro-Democratic
President 2016	6.8%	Pro-Republican
Senate 2018	6.3%	Pro-Republican
Senate 2016	7.1%	Pro-Republican

# Appendix E: CV of Dr. Daryl R. DeFord

A complete version of my CV is attached here, including a list of all publications in the preceding 10 years.

## DARYL R. DEFORD

#### Curriculum Vitae

328 Neill Hall WSU Pullman, WA  $\diamond$  (509) 205–7347 daryl.deford@wsu.edu  $\diamond$  daryldeford.com

#### ACADEMIC APPOINTMENTS

Simons Laufer Mathematics Sciences Research Institute

August 2023 – December 2023

Research Member - Program in Algorithms, Fairness, and Equity

Washington State University, Pullman, WA

August 2020 - Present

Assistant Professor of Data Analytics – Department of Mathematics and Statistics

Massachusetts Institute of Technology, Cambridge, MA

June 2018 - July 2020

Postdoctoral Associate – CSAIL Geometric Data Processing Group

Advisor: Justin Solomon

Tufts University, Medford, MA

June 2018 - July 2020

Visiting Scholar – Jonathan M. Tisch College of Civic Life

Advisor: Moon Duchin

#### **EDUCATION**

Dartmouth College, Hanover, NH

Ph.D. Mathematics

September 2013 - June 2018

Awarded June 2018

Advisor: Dan Rockmore

Dissertation: Matched Products and Dynamical Models for Multiplex Networks

A.M. Mathematics Awarded November 2014

Washington State University, Pullman, WA

August 2010 - May 2013

B.S. in Theoretical Mathematics

Awarded May 2013

Summa Cum Laude

#### RESEARCH PUBLICATIONS

#### **Accepted Papers**

- A30: Does the first-serving team have a structural advantage in pickleball?, (with S. Ethier), Contemporary Mathematics, (to appear 2024).
- A29: Ranking Trees Based on Global Centrality Measures, (with A. Barghi), Discrete Applied Mathematics, 343, 231-257, 2024.
- A28: Multi-Balanced Redistricting, (with E. Kimsey and R. Zerr), Journal of Computational Social Science, 2023.
- A27: Stirling Numbers of Uniform Trees and Related Computational Experiments, (with A. Barghi), Algorithms, 16(5), 2023.
- A26: Maximum a Posteriori Inference of Random Dot Product Graphs via Conic Programming (with D. Wu and D. Palmer), SIAM Journal on Optimization, 32(4), 2527–2551, 2022.
- A25: Random Walks and the Universe of Districting Plans (with M. Duchin), Book Chapter in Political Geography, Birkhäuser, 2022.
- A24: Implementing Partisan Symmetry: A Response to a Response (with N. Dhamankar, M. Duchin, V. Gupta, M. McPike, G. Schoenbach, K. W. Sim), Political Analysis, 31(3), 332-334, 2023.
- A23: Implementing Partisan Symmetry: Problems and Paradoxes (with N. Dhamankar, M. Duchin, V. Gupta, M. McPike, G. Schoenbach, K. W. Sim), Political Analysis, 31(3), 305-324, 2023.

- A22: Empirical Sampling of Connected Graph Partitions for Redistricting (with L. Najt and J. Solomon), Physical Review E, 104(6), 064130, 2021.
- A21: Partisan Dislocation: A Precinct-Level Measure of Representation and Gerrymandering (with N. Eubank and J. Rodden), Political Analysis, 1-23, doi:10.1017/pan.2021.13, 2021.
- A20: Colorado in Context: Congressional Redistricting and Competing Fairness Criteria in Colorado (with J. Clelland, H. Colgate, B. Malmskog, and F. Sancier-Barbosa), Journal of Computational Social Science, doi:10.1007/s42001-021-00119-7, 2021.
- A19: ReCombination: A family of Markov chains for redistricting (with M. Duchin and J. Solomon), Harvard Data Science Review, 3(1), 2021.
- A18: Medial Axis Isoperimetric Profiles (with J. Solomon and P. Zhang), Computer Graphics Forum, 39(5), 1-13, 2020.
- A17: On the Spectrum of Finite, Rooted Homogeneous Trees (with D. Rockmore), Linear Algebra and its Applications, 598, 165-185, 2020.
- A16: Competitiveness Measures for Evaluating Districting Plans (with M. Duchin and J. Solomon), Statistics and Public Policy, 7(1), 69-86, 2020.
- A15: Mathematics of Nested Districts: The Case of Alaska (with S. Caldera, M. Duchin, S. Gutenkust, and C. Nix), Statistics and Public Policy, 7(1), 39-51, 2020.
- A14: Aftermath: The ensemble approach to political redistricting (with J. Clelland and M. Duchin), MAA Math Horizons, 28(1), 34-35, 2020.
- A13: Total Variation Isoperimetric Profiles (with H. Lavenant, Z. Schutzman, and J. Solomon), SIAM J. Appl. Algebra Geometry, 3(4), 585-613, 2019.
- A12: Spectral Clustering Methods for Multiplex Networks (with S. Pauls) Physica A: Statistical Mechanics and its Applications, 533, 121949, 2019.
- A11: Redistricting Reform in Virginia: Districting Criteria in Context (with M. Duchin), Virginia Policy Review, 12(2), 120-146, 2019.
- A10: A New Framework for Dynamical Models on Multiplex Networks (with S. Pauls), Journal of Complex Networks, 6(3), 353-381, 2018.
- A9: Cyclic Groups with the same Hodge Series, (with P. Doyle), Revista de la Uniòn Matemática Argentina, 59(2), 241–254, 2018.
- A8: Multiplex Dynamics on the World Trade Web, Proc. 6th International Conference on Complex Networks and Applications, Studies in Computational Intelligence, Springer, 1111–1123, 2018.
- A7: Random Walk Null Models for Time Series Data, (with K. Moore), Entropy, 19(11), 615, 2017.
- A6: Enumerating Tilings of Rectangles By Squares, Journal of Combinatorics, 6(3), 339-351, 2015.
- A5: Enumerating Distinct Chessboard Tilings, Fibonacci Quarterly, 52(5), 102-116, 2014.
- A4: Pulsated Fibonacci Sequences (with K. Atanassov and A. Shannon), Fibonacci Quarterly, 52(5), 22-27, 2014.
- A3: Seating Rearrangements on Arbitrary Graphs, Involve: A Journal of Mathematics, 7(6), 787-805, 2014.
- A2: Empirical Analysis of Space-Filling Curves for Scientific Computing Applications (With A. Kalyanaraman), Proc. 42nd International Conference on Parallel Processing, 170-179, 2013.
- A1: Counting Rearrangements on Generalized Wheel Graphs, Fibonacci Quarterly, 51(3), 259-273, 2013.

#### **Preprints**

- P5: Observations on SMC for graph partitions (with S. Cannon and M. Duchin), (2023).
- P4: Labeled Graph Rearrangements on Matched and Star Products, (with A. Barghi), (2022).
- P3: Complexity and Geometry of Sampling Connected Graph Partitions (with L. Najt and J. Solomon), arXiv: 1908.08881, (2019).
- P2: Fourier Transforms on  $SL_2(\mathbb{Z}/p^n\mathbb{Z})$  and Related Numerical Experiments (with B. Breen, J. Linehan, and D. Rockmore), arXiv:1710.02687, (2017).
- P1: A Random Dot Product Model for Weighted Networks (with D. Rockmore) arXiv: 1611.02530, (2016).

#### **Technical and Expert Reports**

- T9: Amicus Brief of Computational Redistricting Experts (with. J. Amunson, A. Becker, D. Gold, and S. Hirsch), Merrill vs. Milligan, Supreme Court, 2022.
- T8: Expert and Rebuttal Reports in Pennsylvania Commonwealth Court, for Math/Science Petitioners, 2022.
- T7: Expert and Rebuttal Reports in Wisconsin State Supreme Court, for Citizen Mathematicians and Scientists, 2021 and 2022.
- T6: Ensemble Analysis for 2021 Legislative Redistricting in Colorado, First and Second Staff Plans (with J. Clelland, B. Malmskog, and F. Sancier-Barbosa), Colorado in Context Report, 2021.
- T5: Ensemble Analysis for 2021 Congressional Redistricting in Colorado (with J. Clelland, B. Malmskog, and F. Sancier-Barbosa), Colorado in Context Report, 2021.
- T4: Comparison of Districting Plans for the Virginia House of Delegates (with M. Duchin and J. Solomon), MGGG Technical Report, 2019.
- T3: Amicus Brief of Mathematicians, Law Professors, and Students (with M. Duchin and G. Charles et al.), Rucho v. Common Cause, Supreme Court, 2019.
- T2: Study of Reform Proposals for Chicago City Council (with M. Duchin et al.), MGGG Technical Report, 2019.
- T1: An Application of the Permanent–Determinant Method: Computing the Z-Index of Arbitrary Trees, WSU Department of Mathematics Technical Report Series 2013 #2, 2013.

#### TEACHING EXPERIENCE

#### Washington State University

Pullman, WA

Assistant Professor

Fall 2020 - Present

• Designed syllabi and daily lectures. Wrote and graded homework, quizzes, and exams. Fully responsible for course content and material.

#### MATH 588 - Topics in Computational Mathematics

Spring 2024

Graduate topics course focusing on discrete and computational methods for modeling social systems with an emphasis on social network analysis and the mathematics of political redistricting.

#### STAT 437 - High Dimensional Data Learning and Visualization

*Spring 2024* 

Data visualization, metric-based clustering, probabilistic and metric-based classification, algebraic and probabilistic dimension reduction, inferential methods, analysis of non-Euclidean data.

#### Math 555 - Topics in Combinatorics: The Probabilistic Method

Spring 2023

Graduate topics course focusing on combinatorial proof techniques including probabilistic methods for nonconstructive proofs in graph theory.

#### Math 587 - Representation Theory

Fall 2022

Graduate topics course covering representations of finite groups with a particular emphasis on  $S_n$ , character theory, and basic Lie representations, with applications to Fourier analysis, spectral graph theory, and random walks.

#### STAT 536 - Statistical Computing

Fall 2022

Modern computing methods for statistical application and research including generation of random variables, Monte Carlo simulation, bootstrap and jackknife methods, EM algorithm, and Markov chain Monte Carlo methods.

#### Math 533 - Teaching College Mathematics

Fall 2022

Theory and practice of mathematics instruction at the collegiate level. This course is designed to support TAs in the Department of Mathematics and Statistics. This includes not just pedagogical development but also provides a broader introduction to the various cultures of academia.

Spring 2022

Fundamental course on numerical computation, including: finding zeroes of functions, approximation and interpolation, numerical integration, numerical solution of ordinary differential equations, and numerical linear algebra.

#### STAT 419 - Introduction to Multivariate Statistics

Fall 2021

Introductory course covering multidimensional data, multivariate normal distribution, principal components, factor analysis, clustering, and discriminant analysis.

#### Data 115 - Introduction to Data Analytics

Fall 2020, 2021 Spring 2021

Basic techniques and methodology of data science, with an emphasis on data processing and software tools. This course provides a foundation for beginning data analytics majors as well as students from across the university who are looking to develop data and quantitative literacy.

Math 581 - Topics in Math (Computational Methods in Complex Networks) Fall 2020 Introduction to computational methods and software for analyzing complex systems as well as applications of partition sampling to political redistricting.

#### Math 599 - Professional Development

Fall 2020, 2021, 2022

This course helps advanced graduate students prepare for the academic and industry job markets, providing advice and feedback about preparing job materials, practice interviews and talks, and other professional preparation.

#### Metric Geometry and Gerrymandering Group

Cambridge, MA

VRDI Instructor

Case 2023AP001399

Summer 2018, 2019

· Organized and led student research groups during an eight week summer program on political redistricting for 80+ graduate and undergraduate students. Met with students daily and both generated and supervised a wide variety of research projects in computational, mathematical, and political topics.

**Tufts University** Medford, MA Co-Instructor Spring 2019

Co-taught STS 10: Reading Lab on Mathematical Models in Social Context. This is a reading and discussion based course focused on providing an STS perspective to students who are taking technicallyfocused modeling classes.

#### Massachusetts Institute of Technology

Cambridge, MA

IAP Instructor

January 2019

· Developed a four-week course on computational methods for political redistricting. The course incorporated cutting edge mathematical and computational techniques for analyzing gerrymandering.

#### **Dartmouth College**

Hanover, NH

Graduate Instructor

September 2015 - May 2018

· Designed syllabi and daily lectures. Wrote and graded homework, quizzes, and exams.

Math 36/QSS 36 - Mathematical Modeling in the Social Sciences

Fall 2017

Data driven course exploring mathematical models and analysis techniques

UNSG 100 - Graduate Ethics Seminar

Fall 2017, 2016, 2015

Seminar on ethical and professional issues in science and mathematics

Math 8 - Calculus of Functions of one and Several Variables

Winter 2017

Second term calculus course covering infinite series, vector functions, and partial derivatives Math 1 - Calculus with Algebra

Introductory calculus course with an emphasis on limits and differentiation

Fall 2015

Teaching Assistant

Case 2023AP001399

September 2013 - June 2015

· Held tutorial sessions three times per week. Graded guizzes and exams.

Math 23 - Differential EquationsSpring 2015Math 22 - Linear Algebra with ApplicationsFall 2014Math 3 - CalculusWinter 2014Math 12 - Calculus PlusFall 2013

#### Washington State University

Pullman, WA

Undergraduate Teaching Assistant August 2012 - May 2013

· Held tutorial sessions and graded homework and exams. Supervised a mathematical computing lab.

Math 320 - Modern AlgebraSpring 2013Math 330 - Secondary TeachingSpring 2013Math 315 - Differential EquationsFall 2012

#### RESEARCH SUPERVISION

#### Postdoctoral Mentor

- Dr. Zhanzhan Zhao (SLMath Postdoc Fall 2023)
  - Topic: Algorithms, Fairness, and Equity

#### PhD Advisor

- Md. Mahedi Hasan (WSU Statistics 2022 )
  - Topic: Change point detection in RDPG models
- Weiwei Xie (Coadvised with Dean Johnson WSU Statistics 2022 )
  - Topic: Ordinal Pattern Analysis for Time Series
- Patrick Gambill (Coadvised with Bala Krishnamoorthy WSU Mathematics 2022 )
  - Topic: 3D Printing Path Design
- Phousawanh Peaungvongpakdy (WSU Mathematics 2022 )
  - Topic: Mathematical and Computational Democracy
- Swarnita Chakraborty (Coadvised with Jan Dasgupta WSU Statistics 2021 2023)
  - Thesis: A Novel Approach to Multiple Hypothesis Testing Under Dependence and Insights for Inference on Random Dot Product Networks

#### PhD Committee Member

- Nathaniel Parks (WSU Math 2023-)
- Yanan Tang (WSU Statistics 2022-)
- Ben Hellwig (WSU Math 2022-)
- Wiriyaporn Laaied (WSU Statistics 2022-)
- Stephanie Kane (WSU IIDP 2021-)
- Katrina Sabochick (WSU Math 2021-2023)
- Faizah Alanazi (WSU Math 2021)

#### MS Project Supervisor

- Qingwei Qiao (WSU Stats 2023 )
  - Project: NLP Prediction of Market Indices
- Garrett Kepler (WSU Applied Math 2023 )
  - Project: Spectral Properties of Network Null Models
- Yang Hu (WSU Applied Math 2023 )
  - Project: Communication of applied statistical data analysis
- Sahil Patil (WSU Stats 2023 )
  - Project: Impact of adapting annealing schedules on a pricing algorithm
- Jackie Carlton (WSU MS Applied Math 2023-)
  - Project: New metrics for evaluating partisan fairness of districting plans
- Anastasia Vishnevskaya (WSU MS Statistics 2021-2022)
  - Project: Exploring China's Twiplomacy: Social Network and Sentiment Analysis of the 'Chinese Embassy in the US' Twitter Account
- James Asare (WSU MS Applied Math 2020-2021)
  - Project: Analysis of Optimized Plans for School Redistricting

#### MS Committee Member

- David Rice (WSU MS Statistics 2023-)
- Chuhua Ying (WSU MS Statistics 2023-)
- Sita Khanal (WSU MS Statistics 2023-)
- Star Oje (WSU MS Statistics 2023-)
- Nathaniel Parks (WSU MS Math 2023-)
- Tamara Trbojevic (WSU MS Applied Math 2022-2023)
- Shivani Sawant (WSU MS Statistics 2022-2023)
- Almira Salimgarieva (WSU MS Statistics 2022-2023)
- Jiwen Qiu (WSU MS Statistics 2022-2023)

#### **BS** Project Supervisor

- Kallie Distler (WSU Psychology 2022-2023)
  - Project: Null Models for Social Network Analysis of Elementary School Students
- Eric Johnson (WSU Math 2022-2023)
  - Project: Dynamics of Voting Networks: Implications for Fairness, Representation, and Accountability
- Zhiyaun (Freeman) Chen (WSU Data Analytics 2022)
  - Project: Spatial Influences on Vote Modeling in Washington State
- Elliot Kimsey (WSU Data Analytics 2021-2022)

- Project: Analysis of Malapportionment on Washington State Dual Graphs
- Karthik Ayyalasomayajula (WSU Data Analytics 2022)
  - Project: Geo-Spatial Analysis of Ranked Choice Voting in Maine Congressional Elections
- Rishabh Chandra (MIT EECS UROP 2019-2020)
  - Project: Reinforcement Learning for Graph Partitions

#### **High School Project Supervisor**

- Harrison Roth (Paul D. Schreiber Senior High School Math Research Program 2022-2023)
  - Project: Gerrymandering: Properties of Nested Districts with Application to Illinois
- Brian Pae (Collegiate School Science and Engineering Research Program 2022-2023)
  - Project: Computational Redistricting Analysis of Incumbency in New York

#### EDUCATIONAL OUTREACH

### AMS Engaged Pedagogy Series

Zoom

Instructor Spring 2023

· Designed and presented interactive course materials on gerrymandering and computational redistricting for instructors across the country together with other experts in the Mathematical Foundations for Democratic Processes program.

# CISER Workshop on Python for Social Network Analysis Instructor

Pullman, WA March 2023

· Designed and presented interactive course materials on network science and the networkx package in Python. The interdisciplinary approach attracted students from eleven different departments around the WSU campus.

#### UW Data Science for Social Good

Seattle, WA

Project Lead

 $Summer\ 2021$ 

· Designed and supervised a research project for four data science fellows on applications of ensemble methods to initial districting plan evaluation. The fellows gave a public presentation of their work and developed a user guide "Applying GerryChain: A Users Guide for Redistricting Problems" with accompanying website, case studies, and code examples to demonstrate good modeling practives and support other researchers working on these problems.

#### New Hampshire State Math Team

Manchester, NH

Math Team Coach

Fall 2018-2020

· Designed practice problems and preparatory exercises for the AMC exams, ARML, MMATH, and HMMT. Led monthly problem solving sessions and group activities.

#### LATEX Workshops

Hanover, NH

Organizer

Fall 2016-May 2018

· Designed and presented a series of eleven one hour—long and two three hour—long workshops on mathematical typesetting in LaTeX with D. Freund and K. Harding.

### Crossroads Academy Math Team

Lyme, NH

Math Team Coach

Case 2023AP001399

September 2015 - May 2018

• Designed practice problems and preparatory exercises for the AMC exams, MathCounts, and MathLeague. Led weekly problem solving sessions and group activities. During 2015–17, the Crossroads team twice won the Chapter and State MathCounts and MathLeague competitions and placed first in Northern New England on the AMC-8.

#### New Hampshire State MathCounts Team

Lyme, NH

Math Team Coach

March 2017 - May 2017

· Designed practice problems and preparatory exercises for the national MathCounts exam. Led biweekly problem solving sessions and group activities. Students competed in the national competition in Orlando, Florida.

# Johns Hopkins Center for Talented Youth Science and Technology Series Hanover, NH Workshop Leader

· Developed and presented hour-long workshops for high school students.

Binary and Barcodes (with D. Freund)

Forensic Accounting

Modern Cryptography (with D. Freund)

April 2017

April 2016

October 2014

#### Dartmouth College Exploring Mathematics Camp

11. International Linear Algebra Society, Zoom

Applications of Linear Algebra to Graph Theory and Network Science

Hanover, NH

Match 2023

 $Co ext{-}Instructor$ 

· Organized and presented week long math camps for high school students.

Mathematics of Games

Cryptography

August 2015

July 2015

#### RESEARCH PRESENTATIONS

#### **Talks**

Tan	15	
1.	WUSTL Physics Theory Seminar, St. Louis, MO	November 2023
	Markov Chain Sampling of Graph Partitions for Analyzing Political Geometries	
2.	SLMath Network Science Seminar, Berkeley, CA	$November\ 2023$
	Multi-resolution Network Structures in Census Data	
3.	WSU-PNNL Data Day, Richland, WA	$November\ 2023$
	Multi-Objective Optimization for Computational Redistricting Problems	
4.	UI Math and Stats Colloquium, Moscow, ID	$November\ 2023$
	Political Geometries	
5.	SLMath Workshop on Randomization, Neutrality, and Fairness, Berkeley, CA	$October\ 2023$
	Optimization, Sampling, and Evaluating Non-Partisan Justifications	
6.	INFORMS Annual Meeting, Phoenix, AZ,	$October\ 2023$
	Multi-balanced Redistricting And Within-cycle Malapportionment In Computation	nal Redistricting
7.	SLMath Redistricting Working Group, Berkeley, CA	$October\ 2023$
	Introduction to MCMC (with Scrabble)	
8.	SLMath Connections Workshop 5 Minute Intro, Berkeley, CA	$August\ 2023$
	Mathematical and Computational Redistricting	
9.	MGGG Summer Program, Boston, MA	$June \ 2023$
	Computational Redistricting	
10.	IISE Annual Meeting, New Orleans, LA	$May\ 2023$
	$Multi-Objective\ Optimization\ for\ Evaluating\ Within-Cycle\ Malapportion ment$	

12.	Fu Lab Seminar, Dartmouth College, Hanover, NH	February	2023
13.	Case Studies in Computational Redistricting Joint Mathematics Meetings, Boston, MA	January	2023
14.	- '	September	2022
15.		September	2022
16.	Panelist: How to improve redistricting data sourcing & quality  MGGG Redistricting Lab, Medford, MA  Sampling Complexity and 'Practical' Informacian Naturals Medical	August	2022
17.	Sampling Complexity and 'Practical' Inference on Network Models Permutation Patterns, Valparaiso, IN Enumerating Orderings on Matched Product Graphs	June	2022
18.	WSU Common Read Program, Pullman, WA Algorithmic Bias and Modern Inequalities	April	2022
19.	PiMUC Plenary Talk, Pullman WA Political Geographies: Graphs, Geometry, and Gerrymandering	April	2022
20.	SIAM Minisymposium "Mathematics of Complex Systems" JMM 2022, Seattle, V Initial Districting Design with Markov Chain Ensembles	VA April	2022
21.	Mathematics plus Democracy Seminar, NYU, New York, NY Partisan Dislocation, Competitiveness, and Designing Ensembles for Redistricting	March Analysis	2022
22.	Fu Lab Seminar, Dartmouth College, Hanover, NH Partisan Dislocation, Competitiveness, and Designing Ensembles for Redistricting	February	2022
23.	D4 Seminar PNNL-WSU, Pullman, WA Sampling Complexity and 'Practical' Inference on Network Models	February	2022
24.	ADSA Annual Conference, Zoom  Democratizing Districting	February	2022
25.	Carter et al. v. Chapman et al. PA Commonwealth Court, Harrisburg, PA  Expert testimony for Gressman Math and Science Petitioners	January	2022
26.	Analysis Seminar, Pullman, WA Introduction to Graphons I and II	December	2021
27.	PPPA Research Colloquium, Pullman, WA Computational Methods for Evaluating Districting Plans	November	2021
28.	INFORMS Annual Meeting, Zoom Algorithms And Analysis For Centered Redistricting Plans	October	2021
29.	WSU Math Club, Pullman, WA Graphs, Geometry, and Gerrymandering	October	2021
30.	Civic Hackathon, Madison, WI Introduction to Computational Redistricting	September	2021
31.	Harvard Redistricting Algorithms, Law, and Policy Cambridge, MA Technical State of the Art for Computational Redistricting	September	2021
32.	ASA Joint Statistical Meeting, Zoom  Computational Methods for Assessing Political Redistricting Reforms	August	2021
33.	New Mexico Redistricting Commission, Santa Fe, NM  Markov chain ensemble metrics for evaluation of redistricting plans	July	2021
34.	Colorado College Summer Program, Colorado Springs, CO Computational Redistricting Analysis	June	2021
35.	WSU Seminar in Statistics, Pullman, WA Ensemble Analysis for the 2020 Redistricting Cycle	April	2021
36.	Princeton Gerrymandering Project, Princeton, NJ Computational Redistricting in 2021	March	2021
37.	Combinatorics, Linear Algebra, and Number Theory, WSU, Pullman, WA Gerry-Matchings and Pair-y-Mandering	March	2021

Short Course: Mathematical and Computational Methods for Complex Social Systems  39. INFORMS Special Session on Fairness in Operations Research, Baltimore, MD Computational Methods For Assessing Districting Plans  40. WSU Seminar in Statistics, Pullman, WA Statistical and Computational Methods for Assessing Political Redistricting  41. Pi MU Epsilon Lecture, St. Michael's College, Colchester, VT October 2020 Graphs, Geometry, and Gerrymandering  42. ADSA Annual Meeting, Zoom October 2020 Geospatial Data for Political Redistricting Analysis  43. Common Experience Lecture, Texas State University, San Marcos, TX October 2020 Graphs, Geometry, and Gerrymandering  44. Combinatorics, Linear Algebra, and Number Theory, WSU, Pullman, WA Representations of $SL_2(\mathbb{Z}/p^n\mathbb{Z})$ and spectral properties of Bethe trees  45. CGAD-GTOpt Seminar, Washington State University, Pullman, WA, Geometric and Optimization Problems Motivated by Political Redistricting  46. Redistricting Conference 2020, Duke University, Durham, NC, Multiresolution Redistricting Algorithms  47. Math Department Colloquium, College of Charleston, Charleston, SC. Geospatial Data, Markov Chains, and Political Redistricting  48. Math Department Colloquium, Washington State University, Pullman, WA. Geospatial Data, Markov Chains, and Political Redistricting  49. JMM 2020, Denver, CO. January 2020 Markov chains for sampling connected graph partitions  50. Math Department Colloquium, Pacific University, Forest Grove, OR. January 2020 The Mathematics of Nested Legislative Districts  51. MIT Graphics Annual Retreat, North Falmouth, MA. October 2019 Connected Graph Partitions and Political Districting  52. Topology, Geometry and Data Seminar, Ohio State University, Columbus, OH. September 2019 Graphs, Geometry, and Gerrymandering  53. Math Department Colloquium, Denison University, Granville, OH. September 2019 Graphs, Geometry, and Gerrymandering  54. Math Department Colloquium, Oberlin College, Oberlin, OH. September 2019 Graphs, Geometry, and Gerrymandering  55
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Graphs, Geometry, and Gerrymandering
57. Applied Math Seminar, University of Massachusetts Lowell, Lowell, MA. September 2019  Hardness results for sampling connected graph partitions with applications to redistricting
58. Math Department Colloquium, Yale University, New Haven, CT.  **August 2019** **Mathematical Challenges in Neutral Redistricting**
59. Voting Rights Data Institute Seminar, Cambridge, MA.  June 2019
A Friendly Introduction to Discrete MCMC  60. Voting Rights Data Institute Seminar, Cambridge, MA.  June 2019
Graphs and Networks: Discrete Approaches to Redistricting 61. Math Department Colloquium, Dartmouth College, Hanover, NH.  April 2019
Total Variation Isoperimetric Profiles and Political Redistricting 62. ACM Seminar, Dartmouth College, Hanover, NH.  April 2019
Hardness results for sampling connected graph partitions with applications to redistricting
63. Unrig Summit Masterclass, Nashville, TN.  Legal and Math Deep Dive: Gerrymandering and Redistricting  March 2019

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64.	MIT Graphics Seminar, Cambridge, MA.	March 2019
	Computational Challenges in Neutral Redistricting	
65.	JMM 2019, Baltimore, MD.	January 2019
	Matched Products and Stirling Numbers of Graphs	, and the second
66.	Societal Concerns in Algorithsm and Data Analysis, Weizmann Institute of Science, Rehovot, Israel	ael. December 2018
	Computational Problems in Neutral Redistricting	
67.	Math and Law of Redistricting, Radcliffe Institute, Cambridge, MA.	December 2018
	GerryChain and MCMC tutorials	
68.	Math Colloquium, Tufts University, Medford, MA.	November 2018
	Matched Products and Stirling Numbers of Graphs	
69.	MIT Graphics Annual Retreat, Dedham, MA.	October 2018
	Mathematical Challenges in Neutral Redistricting	
70.	SAMSI Workshop on Quantitative Redistricting, Duke University, Durham,	NC. October 2018
	Compactness Profiles and Reversible Sampling Methods for Plane and Grap	ph Partitions
71.	Election Teach-in, SMFA, Boston, MA.	October 2018
	Computational Challenges in Political Redistricting	
72.	STS Seminar, Tufts University, Cambridge, MA.	September 2018
	Mathematical Modeling of Social Connections	1
73.	Voting Rights Data Institute Seminar, Cambridge, MA.	June 2018
	Introduction to Monte Carlo Methods	
74.	Mathematics Colloquium, University of Central Florida, Orlando, FL.	February 2018
	Dynamical Models for Multiplex Data	,
75.	Mathematics Colloquium GVSU, Grand Valley, MI.	February 2018
	Random Walk Null Models for Time Series	, and the second
76.	Omidyar Fellowship Presentation, Santa Fe, NM.	January 2018
	Mathematical Embeddings of Complex Systems	, and the second
77.	Mathematics Colloquium at University of San Fransisco, San Fransisco, CA	January 2018
	Dynamical Models for Multiplex Data	v
78.	Mathematics Colloquium at Providence College, Providence, RI.	January 2018
	Dynamical Models for Multiplex Data	v
79.	JMM, San Diego, CA.	January 2018
	Dynamical Modeling for Multiplex Networks	
80.	International Complex Networks Conference Lyon, France.	December 2017
	Multiplex Dynamics on the World Trade Web	
81.	Physics Colloquium at Washington University, St. Louis, MO.	October 2017
	Spectral Clustering on Multiplex Data	
82.	SIAM Annual Meeting, Pittsburgh, PA.	July 2017
	Permutation Complexity Measures for Time Series	v
83.	Applied and Computational Mathematics Seminar, Hanover NH.	November 2016
	Random Dot Product Models for Weighted Networks	
84.	Inference on Networks: Algorithms, Phase Transitions, New Models and New Data, Santa Fe, NN	M. December 2015
	Dynamically Motivated Models for Multiplex Networks	
85.	Applied Math Days, Troy, NY.	April 2015
	Multiplex Structure on the World Trade Web	-
86.	Graduate Student Combinatorics Conference, Lexington, KY.	March 2015
	Total Dynamics on Multiplex Networks	
87.	Sixteenth International Fibonacci Conference, Rochester, NY.	July 2014
	Enumerating Distinct Chessboard Tilings	,
88.		Quarterly) 2013 - 2018
	Various Tonias	= *

Various Topics
89. Joint Mathematics Meeting, San Diego, CA.

Counting Combinatorial Rearrangements, Tilings with Squares and Symmetric Tilings

Case 2023AP001399

• SURCA Judge

• Core to Career Faculty Fellow (DATA 115)

• Data Analytics Curriculum Committee

2021 -

2020 -

2021-2022

20/11 00	Export Report of Dr. Daryt Delora in Eupport of Wright Filed of 12 20	724 1 ago 31
90.	West Coast Number Theory Conference, Asilomar, CA.	December 2012
91.	Generalized Lucas Bases Young Mathematician's Conference, Columbus, OH.	July 2012
92.	Combinatorial Rearrangements on Arbitrary Graphs Northwest Undergraduate Mathematics Symposium, Portland, OR.	March 2012
93.	Combinatorial Rearrangements on Arbitrary Graphs WSU Graduate Seminar on Combinatorial Geometry, Pullman, WA. Various Topics	(Quarterly) 2012-2013
Pos	ters	
1.	SIAM Workshop on Network Science, Boston, MA.  Generalized Random Dot Product Models For Multigraphs	July 2016
2.	Dartmouth Graduate Student Poster Session, Hanover, NH.  Generalized Dot Product Models for Weighted Networks	April 2016
3.	Dartmouth Graduate Student Poster Session, Hanover, NH.  Multiplex Structures in the World Trade Web	April 2015
	WSU SURCA, Pullman, WA.  Empirical Analysis of Space Filling Curves for Scientific Computing Apple	March 2013 ications
5.	WSU SURCA, Pullman, WA.  Combinatorial Rearrangements, Restricted Permutations, and Matrix Per	April 2012 manents
HONO	ORS AND AWARDS	
•	WSU CAS Early Career Achievement Award for Tenure Track Faculty College-wide award for outstanding accomplishments in research early in t Dartmouth Hannah Croasdale Award College-wide award for the graduating Ph.D. student that best exemplifies the Dartmouth Graduate Student Teaching Award	2018
•	College-wide award for the graduate student who best exemplifies the qualiti	
	Dartmouth Graduate Fellowship	2014–18
	NSF Graduate Research Fellowship: Honorable Mention	2014, 2015
•	Dartmouth GAANN Fellowship	2013
•	WSU Morris Knebelman Outstanding Senior Award	2013
•	WSU Department of Mathematics Outstanding Senior	2013
•	WSU Emeritus Society Award in the Physical Sciences	2013
•	WSU J. Russell and Mildred H. Vatnsdal Memorial Scholarship	2012 2012, 2013
•	WSU SURCA Crimson Award: Computer Science and Mathematics WSU Auvil Undergraduate Scholars Fellowship	2012, 2013 2012
•	WSU Leonard B. Kirschner Scholarship	2012
•	WSU College of Sciences Undergraduate Research Grant	2012
•	Norma C. Fuentes and Gary M Kirk Award for Excellence in Undergradu	
	ESSIONAL SERVICE	2012
	U Service	
•	Data Analytics Scholarly Track Hiring Committee	2023-2024
	STEM Student Engagement Research and Mentoring Program	2022 -
•	Data Analytics Faculty Advisory Board	2022 -
•	Statistics TT Hiring Committee	2022 - 2023
•	Math Club Faculty Advisor	2021 - 2023
	CIDCA Judge	2021 2020

#### Peer Reviewer

- Political Analysis
- Social Forces
- Notices of the AMS
- Royal Society Open Science
- IISE Annual Conference
- AMS American Mathematical Monthly
- Nature Scientific Data
- Operations Research Forum
- Journal of Computational Social Science
- INFORMS Journal on Applied Analytics
- Proceedings of the National Academy of Sciences (PNAS)
- Algebra Colloquium
- Computers & Graphics
- Election Law Journal
- Transactions on Signal and Information Processing over Networks
- Multiscale Modeling and Simulation: A SIAM Interdisciplinary Journal
- International Conference on Learning Representations (ICLR)
- International Conference on Artificial Intelligence and Statistics (AISTATS)
- AAAI Conference on Artificial Intelligence (AAAI)
- International Conference on Machine Learning (ICML)
- ACM-SIAM Symposium on Discrete Algorithms (SODA)
- Neural Information Processing Systems (NeurIPS)
- Transactions on Pattern Analysis and Machine Intelligence (TPAMI)
- Chaos: An Interdisciplinary Journal of Nonlinear Science
- Involve: A Journal of Mathematics
- Entropy
- Algorithms
- MATCH Communications in Mathematical and in Computer Chemistry

#### PROFESSIONAL MEMBERSHIPS

• Institute for Mathematics and Democracy

• Society for Industrial and Applied Mathematics (SIAM)

• Fibonacci Association (FA)

• American Mathematical Society (AMS)

• Mathematical Association of America (MAA)

invited April 2022

joined June 2016

joined February 2013

joined April 2012

joined April 2012