

# Using Algorithms to Detect Gerrymandering: ALgorithm-Assisted Redistricting Methodology (ALARM) Project

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# Motivation

- Today's world for quantitative social science:
  - 1 increasing availability of granular data
  - 2 rapid methodological advancement
- Social scientists can and should solve problems of the real world!
- Redistricting as a major policy decision
- How can we use data and algorithms to evaluate redistricting plans?
  - traditional methods: comparison across states and time periods
  - confounded by state-specific political geography and rules
- Use of simulation algorithms
  - 1 obtain a representative sample of redistricting plans under constraints
  - 2 compare the enacted plan with this baseline distribution
- Technological solution to detecting gerrymandering
- Tool for analyzing redistricting

# ALgorithm-Assisted Redistricting Methodology (ALARM)

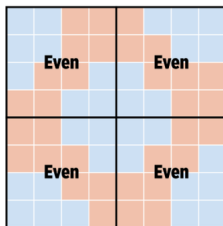


**Developing methodology and tools  
to analyze legislative redistricting.**

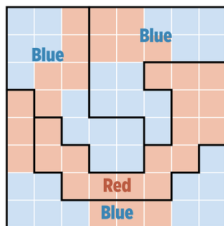
- What we do:
  - ① develop efficient and flexible simulation algorithms
  - ② build open-source software packages for the entire workflow
  - ③ evaluate redistricting plans in the United States and elsewhere
- Goal: empower researchers, policy makers, data journalists, and citizen data scientists with powerful tools

# Redistricting Basics

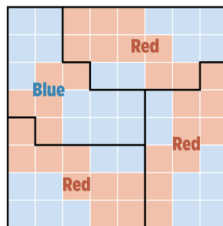
- Classic gerrymandering strategies: **packing** and **cracking**



**Even distribution**  
2 red, 2 blue



**Packing**  
1 red, 3 blue



**Cracking**  
3 red, 1 blue

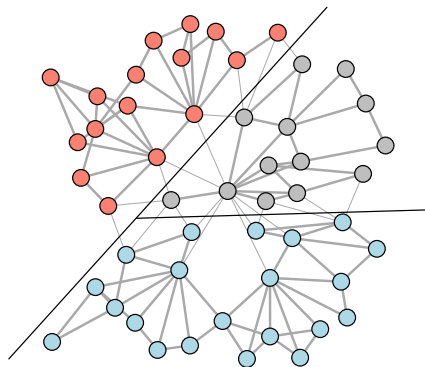
- What has changed:
  - availability of granular data
  - mapping software (e.g., Maptitude, Dave's Redistricting app)
- US Congressional redistricting
  - racial gerrymandering: *Shelby County v. Holder*; *Merrill v. Milligan*
  - partisan gerrymandering: *Rucho v. Common Cause*; *Moore v. Harper*

# Why Use Simulation Algorithm for Redistricting Evaluation?

- Traditional redistricting evaluation
  - 1 compute various fairness metrics
  - 2 compare them across states and over time
- Confounded by differences in political geography and redistricting rules
- Simulation-based redistricting evaluation
  - 1 generate many **alternative plans** under a set of redistricting criteria
  - 2 compare them with a proposed plan to evaluate its properties
- Benefits of simulation approach
  - 1 can control for **state-specific** political geography and redistricting rules
  - 2 **transparency** and ability to isolate a relevant factor
  - 3 mathematical properties  $\rightsquigarrow$  **representative sample** of alternative plans

# Redistricting as a Balanced Graph Partition Problem

50 Precincts, Three Districts



- Efficient **enumeration algorithm** exists (Fifield *et al.* 2020)
- Only applicable to very small redistricting problems
- $9 \times 9 \rightarrow 9$ : equal size  $\approx 700$  trillion, unequal size  $\approx 160$  septillion

# Existing Algorithms

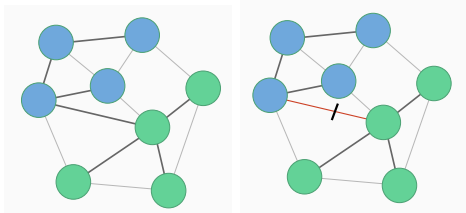
- 1 Constructive Monte Carlo (Chen & Rodden, 2013; Magleby & Mosesson, 2018)
  - randomly select “seeds” and grow districts
  - unknown target population
- 2 **Flip** algorithms (Fifield *et al.*, 2020; Mattingly & Vaughn, 2014; Chikina *et al.* 2017)
  - start with a valid plan and then reassign units on district boundaries
  - target distribution

$$\pi(\xi) \propto \underbrace{\exp(-J(\xi))}_{\text{custom constraints}} \times \underbrace{1_{\xi \text{ connected}}}_{\text{contiguity requirement}} \times \underbrace{1_{\text{dev}(\xi) \leq D}}_{\text{population balance}}$$

- incremental changes; applicable for local exploration
- does not scale; compactness needs to be specified in  $J(\cdot)$

② **Merge-split** algorithms (DeFord *et al.*, 2021; Carter *et al.* 2019)

- randomly choose a pair of adjacent districts, merge them, and split them into two new districts using uniform spanning trees



- target distribution

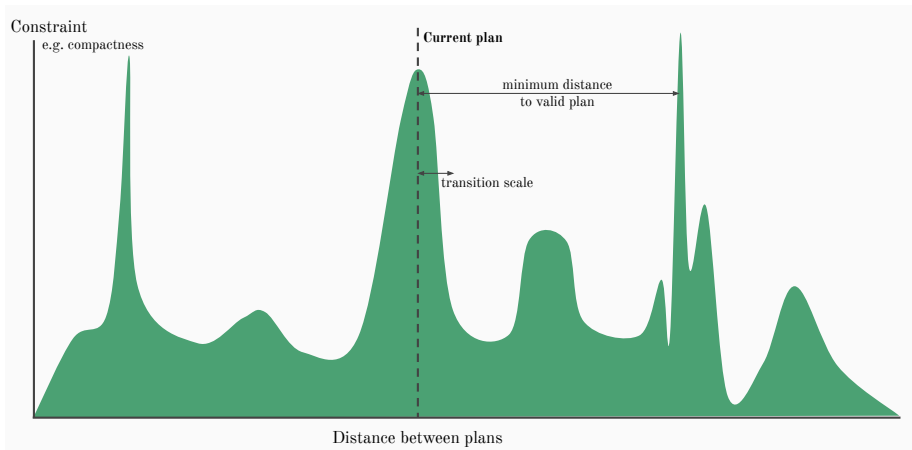
$$\pi(\xi) \propto \underbrace{\tau(\xi)^\rho}_{\text{compactness}} \exp(-J(\xi)) \times \mathbf{1}_{\xi \text{ connected}} \times \mathbf{1}_{\text{dev}(\xi) \leq D}$$

where  $\tau(\xi)$  counts the product of the number of spanning trees in each district of the plan  $\xi$

- relation with edge removal compactness

$$\tau(\xi)^\rho \approx C_1 \exp(-C_2 \rho \text{rem}(\xi)) \quad \text{where} \quad \text{rem}(\xi) = \underbrace{1 - \frac{\sum_{i=1}^n |E_i(\xi)|}{|E(G)|}}_{\text{fraction of edges removed}}$$

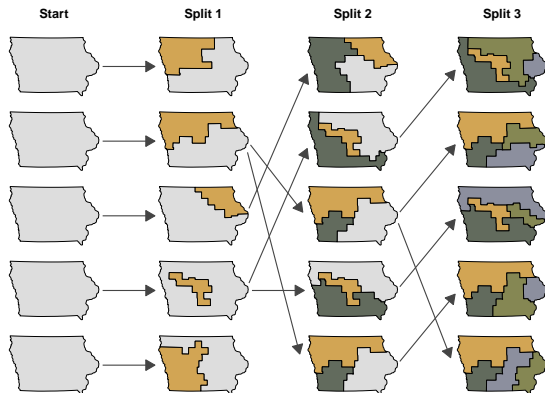
# Challenge of MCMC Algorithms



- simulated annealing, parallel tempering  $\rightsquigarrow$  difficult to apply in practice

# Sequential Monte Carlo (SMC) Algorithm (McCartan and Imai, 2020)

- Start with a blank state **in parallel**, use the spanning tree approach to sample a district at a time, **resample with weights** at each step



- Advantage: unlike MCMC, sampled plans are nearly independent
- Limitation: hard to incorporate plan-wide or region-specific constraints

# The Splitting Procedure

- 1 Generate a uniform spanning tree (Wilson's algorithm)
  - 2 Sort edges by population deviation
  - 3 Sample one edge from top  $k_i$  edges and remove it
  - 4 Check population bounds
- Probability of splitting a new district  $G_i$  from  $\tilde{G}_{i-1}$ :

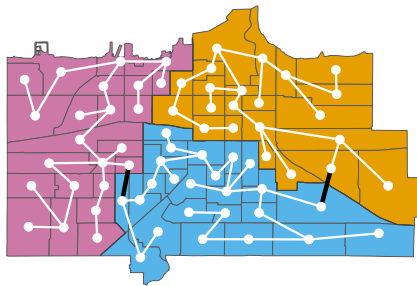
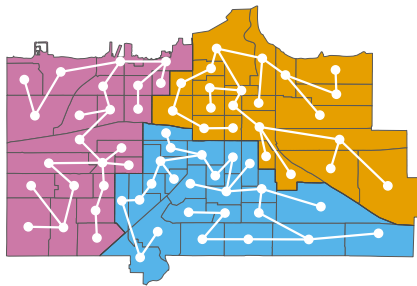
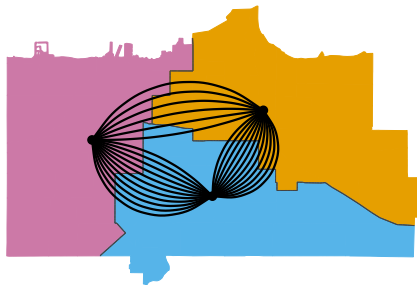
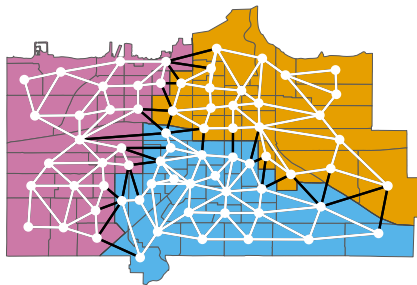
$$\frac{\overbrace{\tau(G_i)\tau(\tilde{G}_i)}^{\text{all possible ways to connect}}}{\underbrace{\tau(\tilde{G}_{i-1})k_i}_{\text{all possible ways to split}}} \times \underbrace{|\mathcal{C}(G_i, \tilde{G}_i)|}_{\text{number of connecting edges}}$$

- Use these probabilities to construct weights

# The SMC Algorithm

- ① Generate  $S$  initial copies of map; set all weights to 1
- ② For  $i \in \{1, 2, \dots, n - 1\}$ :
  - a. Until there are  $S$  successes
    - i. Sample a map according to the weights
    - ii. Split off a new district from each sampled map
    - iii. Reject if population bounds are not met
  - b. Calculate new weights based on splitting probability
- ③ Output complete plans and compute final weights

# Avoiding County Splits through Quotient Multigraph



# SMC Diagnostics

SMC: 1,000 sampled plans of 11 districts on 2,465 units

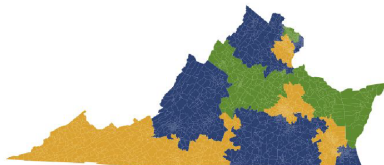
``adapt_k_thresh`=0.985 • `seq_alpha`=0.5`

``est_label_mult`=1 • `pop_temper`=0.01`

Plan diversity 80% range: 0.82 to 0.98

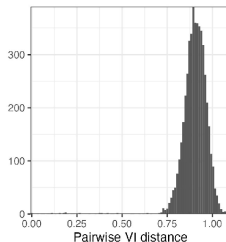
R-hat values for summary statistics:

pop_overlap	comp	dem	e_dem
1.0234	1.0112	1.0053	1.0042

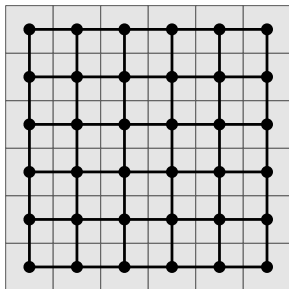


Sampling diagnostics for SMC run 1 of 4 (250 samples)

	Eff. samples (%)	Acc. rate	Log wgt. sd	Max. unique	Est. k
Split 1	242 (97.0%)	20.6%	0.36	245 ( 98%)	10
Split 2	240 (95.8%)	31.2%	0.43	193 ( 77%)	6
Split 3	233 (93.4%)	21.8%	0.49	199 ( 80%)	8
Split 4	231 (92.3%)	29.9%	0.56	196 ( 78%)	5
Split 5	219 (87.6%)	36.1%	0.62	195 ( 78%)	3
Split 6	213 (85.0%)	44.9%	0.67	191 ( 76%)	2
Split 7	224 (89.7%)	15.9%	0.59	189 ( 76%)	7
Split 8	227 (90.8%)	24.2%	0.59	192 ( 77%)	4
Split 9	227 (90.9%)	16.9%	0.60	181 ( 72%)	3
Split 10	228 (91.3%)	3.8%	0.58	174 ( 70%)	2
Resample	166 (66.4%)	NA	0.59	183 ( 73%)	NA

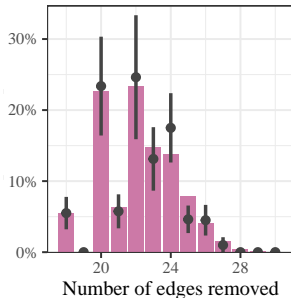


# Validation

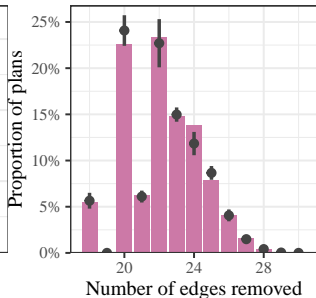


- Divide a  $6 \times 6$  grid into 6 equal-sized districts
- Enumerate 451,206 plans (out of 356 billion)
- Number of edge removed as a target statistic

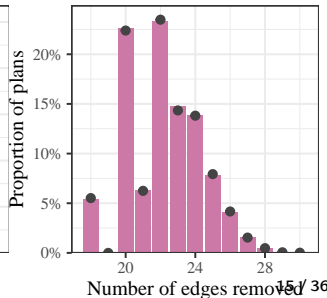
100 samples per run



1,000 samples per run



10,000 samples per run



# 50 State Redistricting Simulations Project

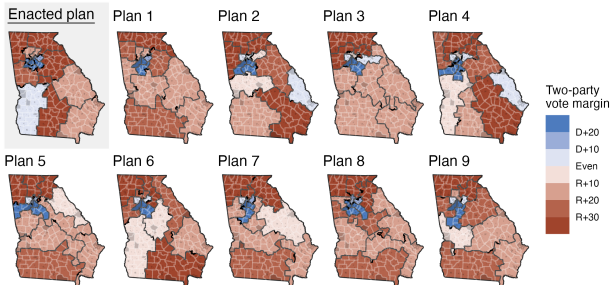


Comprehensive project to simulate alternative congressional redistricting plans for all fifty states.

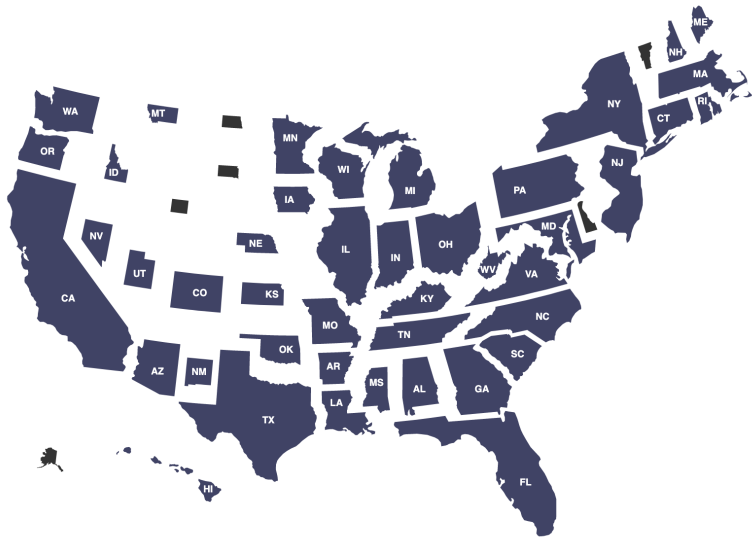
- tidied 2020 Census plus statewide election data from the VEST
- collect state-specific redistricting requirements
- construct algorithmic constraints based on these and traditional redistricting criteria
- 5,000 simulation plans based on SMC
- code and data are available at the Harvard Dataverse

# Georgia Example

- 14 Congressional districts
- According to Georgia's House Legislative and Congressional Reapportionment Committee, districts must:
  - 1 be contiguous
  - 2 have equal populations
  - 3 be geographically compact
  - 4 preserve county and municipality boundaries as much as possible
  - 5 avoid the unnecessary pairing of incumbents
- We attempted to account for everything except incumbency constraint
- Voting rights act (VRA) compliance is tricky



Check out <https://alarm-redist.org/fifty-states/>



States colored **blue** have enacted a congressional map and been fully analyzed, states colored **gray** have enacted a plan but haven't yet been analyzed, or just have a single district (and hence no redistricting), and states colored **red** haven't enacted a plan yet.

# Electoral Modeling

- Precinct-level data from the 2016 and 2020 presidential elections
- Average of the two elections for precinct  $j \rightsquigarrow$  baseline partisanship

$$\hat{D}_j = \underbrace{\frac{1}{2} \left( \frac{D_{16j}}{D_{16j} + R_{16j}} + \frac{D_{20j}}{D_{20j} + R_{20j}} \right)}_{\text{average Democratic vote share}} \times \underbrace{\sqrt{(D_{16j} + R_{16j})(D_{20j} + R_{20j})}}_{\text{(geometric) average turnout}}$$

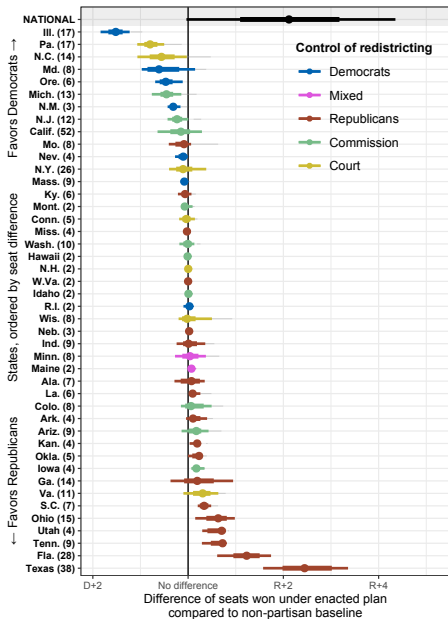
- Model for the Democratic vote share  $y_{it}$  for district  $i$  in election  $t$ :

$$\begin{aligned} \text{logit}(y_{it}) &= \alpha_i + \beta_t + \varepsilon_{it}, \\ \beta_t &\stackrel{iid}{\sim} \mathcal{N}(0, \sigma_\beta^2), \quad \varepsilon_{it} \stackrel{iid}{\sim} t_\nu(0, \sigma_\varepsilon^2), \end{aligned}$$

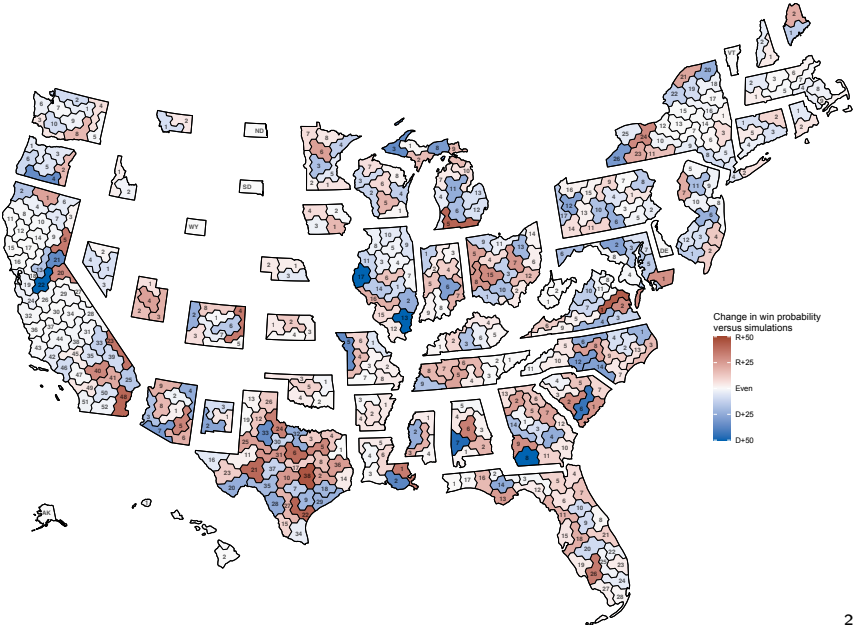
where we fix  $\alpha_i$  to the baseline Democratic vote share and  $(\sigma_\beta^2, \sigma_\varepsilon^2, \nu)$  are estimated using the historical House elections data since 1976

- We then compute  $\alpha_i$  using  $\hat{D}_j$  and simulate  $(\beta_t, \varepsilon_{it})$  under a given (enacted or simulated) redistricting plan

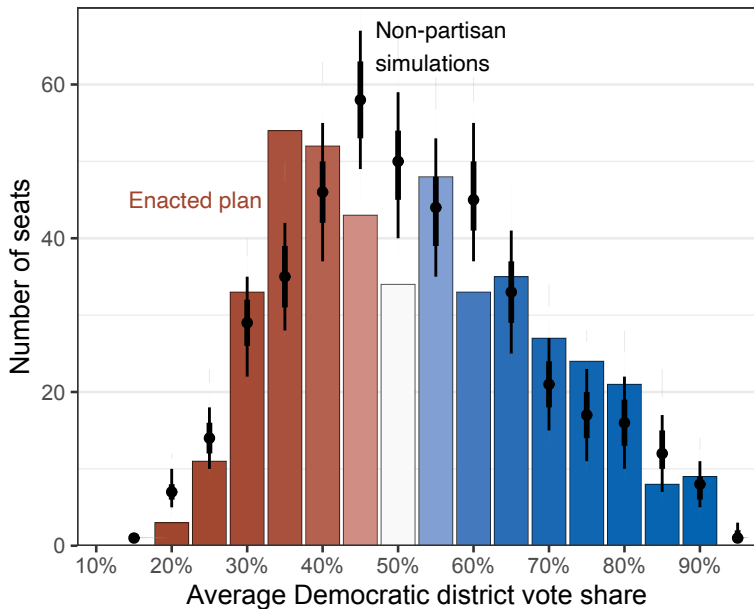
# Widespread Partisan Gerrymandering Cancels Nationally



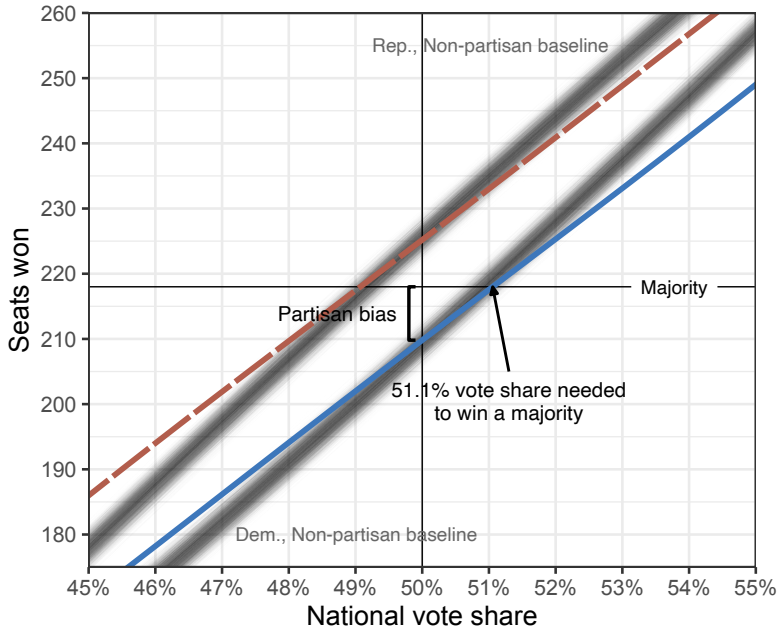
# Map of Partisan Gerrymandering



# Partisan Gerrymandering Reduces Competitiveness



# Partisan Gerrymandering Reduces Responsiveness



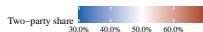
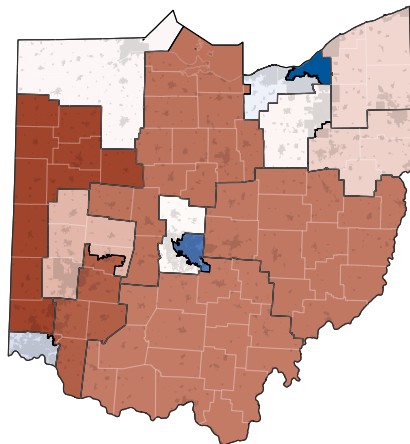
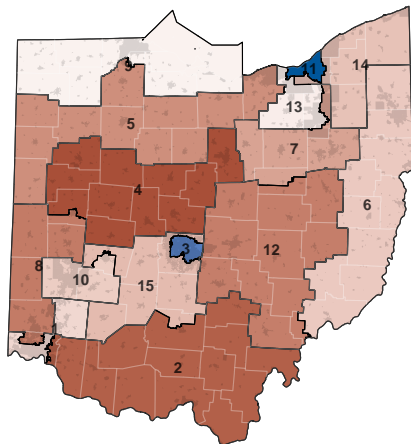
# Application in the Court: Ohio Congressional Redistricting

- Currently 16 districts: 4 Democrats and 12 Republicans
  - 2020 President: Biden 45%, Trump 53%
  - 2018 Senate: Brown 53%, Renacci 47%
- After 2020 Census, the number of seats is reduced to 15 districts
- 2018 Ohio voters passed the constitutional amendment
  - bipartisan support leads to a 10 year map
  - if that fails, it becomes a 4 year map
- Redistricting
  - State Senate and House approved the initial map
  - No bipartisan support  $\rightsquigarrow$  4 year map
  - November 20: Governor DeWine signed the map

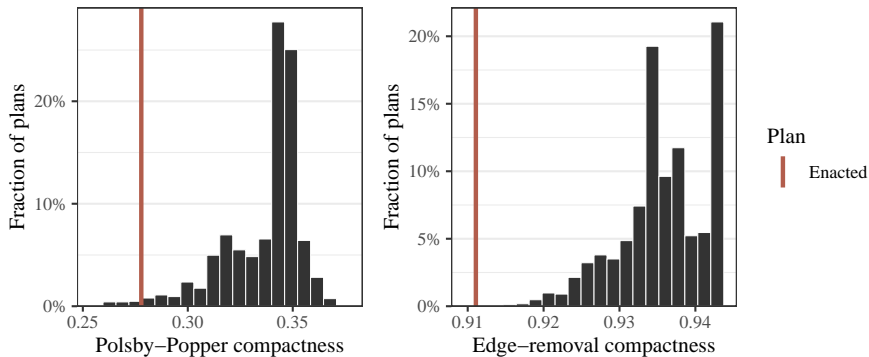
# League of Women Voters of Ohio *et al.* v. Ohio Redistricting Commission, *et al.*

- I served as an expert witness for Relators
- Simulation analysis based on Sequential Monte Carlo algorithm
  - 5,000 alternative plans
  - contiguous and compact districts
  - compliant with the Voting Rights Act (Cleveland)
  - several complicated splitting constraints
  - Section 2(B)(5): out of Ohio's 88 counties,
    - at least 65 counties should not be split
    - no more than 18 counties can be split no more than once
    - no more than 5 counties can be split no more than twice

# The Enacted and Example Simulated Plans

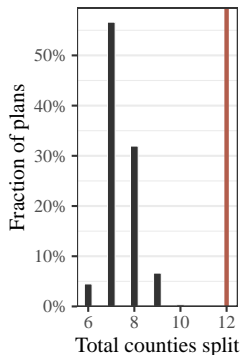
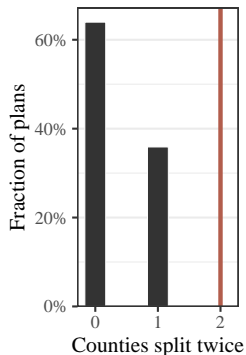
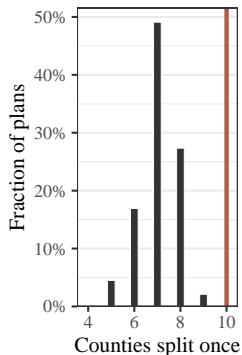


# Compactness



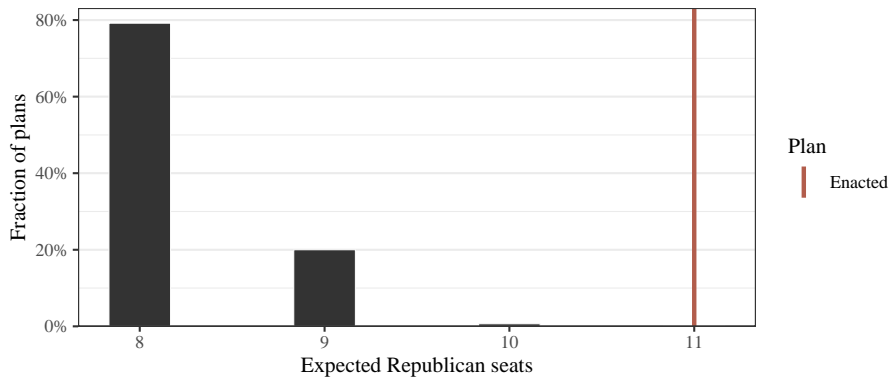
- Polsby-Popper: the ratio of the district area to the area of a circle with the same perimeter
- Edge-removal

# Administrative Boundary Splits



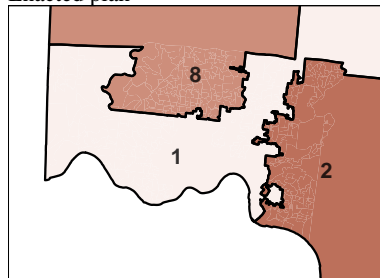
Plan  
Enacted

# Expected Number of Republican Seats

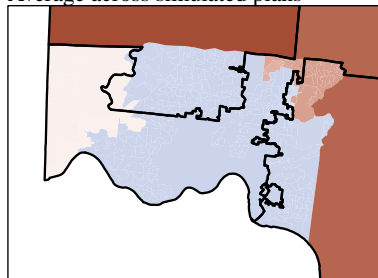


# Cracking: Hamilton County (Cincinnati Area)

Enacted plan



Average across simulated plans



Two-party  
vote share



60%

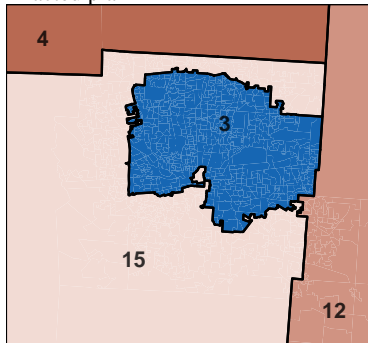
50%

40%

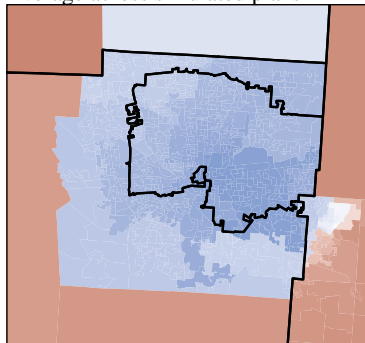
30%

# Packing: Franklin County (Columbus Area)

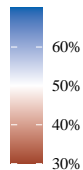
Enacted plan



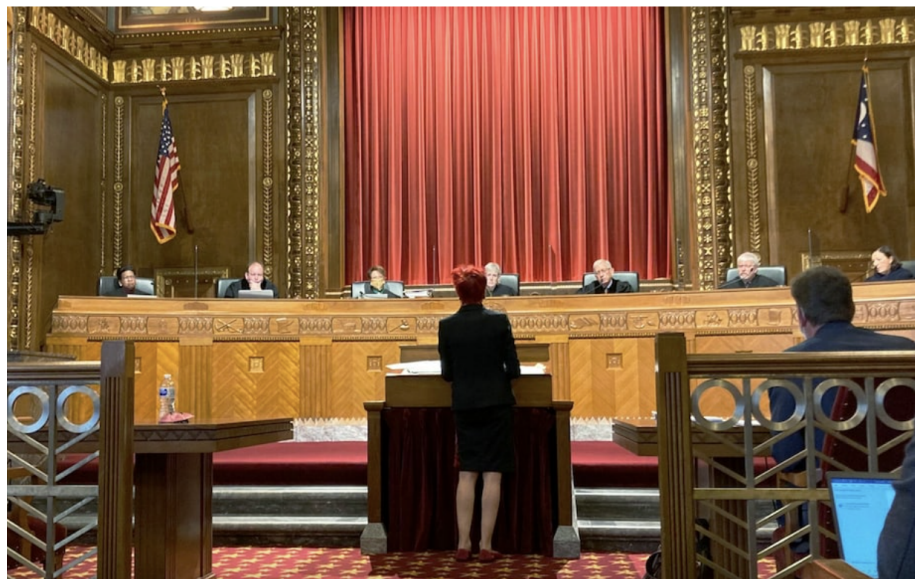
Average across simulated plans



Two-party  
vote share



## Ohio Supreme Court Strikes Down the Enacted Map



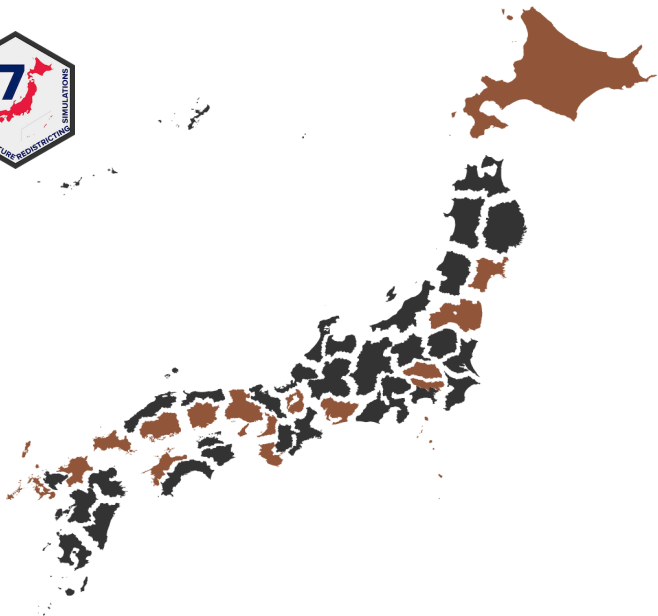
## The Court Opinion

*Id.* at Section 1(C)(3)(a). The above evidence, particularly Dr. Imai's conclusion that the enacted plan will result in, on average, 2.8 more Republican seats than are warranted, shows that the General Assembly's decision to shift what could have been—under a neutral application of Article XIX—Democratic-leaning areas into competitive districts, i.e., districts that give the Republican Party's candidates a better chance of winning than they would otherwise have had in a more compactly drawn district, resulted in a plan that unduly favors the Republican Party and unduly disfavors the Democratic Party.

## Supreme Court: *Merrill v. Milligan*

JUSTICE SOTOMAYOR: I find it interesting that you're touting Dr. Imai's studies when, below, you vehemently objected to his studies on the basis that the studies were incomplete and didn't take into account all of Alabama's guidelines.

# Beyond the United States: Japanese Redistricting



# Concluding Remarks

- Redistricting matters
  - fair representation and policy outcomes
  - competitiveness of districts and responsiveness
  - political polarization
  - state and local offices, education districts, non-US contexts
- How should we stop gerrymandering?
  - independent commission (e.g., Michigan)
  - use of algorithms to detect gerrymandering
- Role of experts
  - legislative process
  - court testimony
- Open problems
  - large-scale redistricting problems (e.g., state legislatures)
  - algorithm-generated redistricting plan proposals
  - communities of interest, impact of redistricting rules