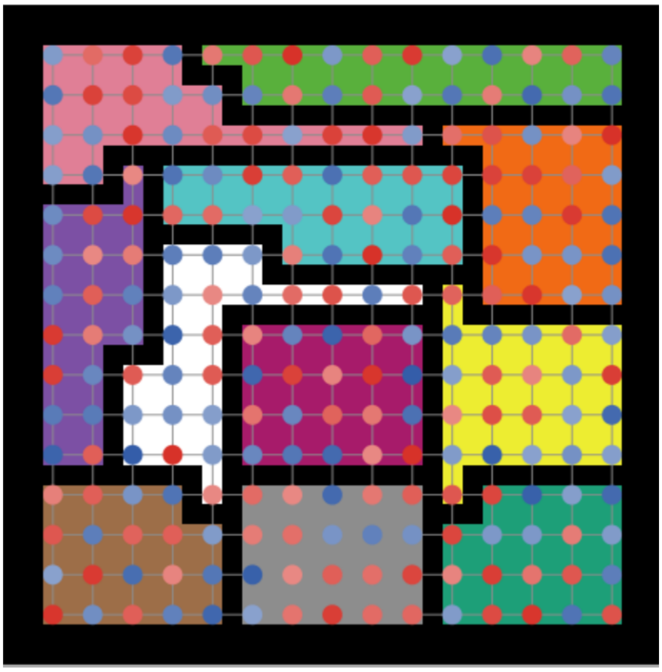
Luke Palmieri
Gowri Prathap

# MODELING VIRGINIA VOTING DISTRICTS



**Abstract** *In US politics, gerrymandering is the practice of drawing the boundaries of electoral districts in a way that either (a) gives one political party an unfair advantage over its rivals (political or partisan gerrymandering), or (b) that dilutes the voting power of members of ethnic or linguistic minority groups (racial gerrymandering). We adapted an existing NetLogo model called NetDistrict[6] to simulate Virginia's voting districts. We added other important information and functions such as a drop-down menu to change the number of districts, reporters that keep track of the percentage of the red and blue areas in the model, and a slider to change partisan score odds of setting up.*

**Keywords** gerrymandering, Virginia, voting, NetLogo, partisan score

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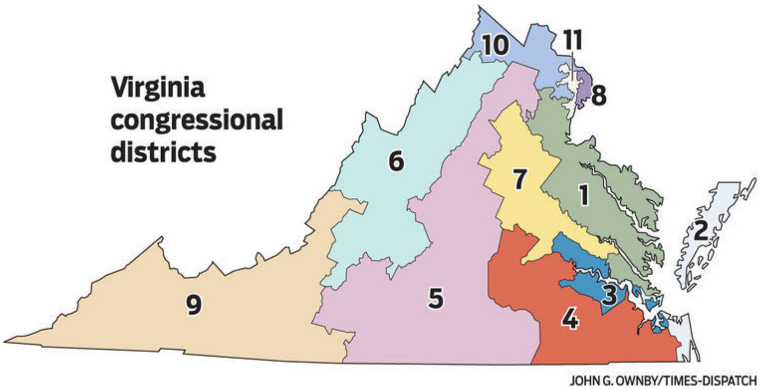



**Figure 1.** Virginia Voting Districts[2]

## 1. Introduction

A key issue within the United States democratic system is gerrymandering - manipulating the process of redistricting so that the partisan or other group doing the gerrymandering gains an electoral advantage from the newly defined districts[3].

Gerrymandering usually involves "cracking" or "packing strategies" (see Figure 2). The US electoral system at both the national and local level involves a first-past-the-post voting system where the top vote receiver is elected. So rearranging the district boundaries enables the party in power to either concentrate or diffuse the voters of the opposing party to win more districts without getting more votes. This strategy is how disproportionate representation occurs.

Gerrymandering represents a threat to the democratic process for several reasons. Fundamentally this strategy undermines the basis of representative democracy and can disproportionately allocate voting power to different groups, destroying "one person one vote"[3]. The effect has often been employed to lower the representation of Black voters that has worsened since the civil rights act was passed. Gerrymandering takes away democratic representation, which further marginalizes and reduces the voting power of Black people.

This strategy is seen strongly in Superfund sites with environmental hazards. A study found during the redistricting process that when black voters are packed into gerrymandered districts, they are gerrymandered out of districts that are farther from Superfund sites[5]. The Black voters are then subject to environmental harm. They are packed into districts of other marginalized people that the government is not responsive to, and the gerrymandering decreases their voting power. It prevents congressional representation and policies that fund the clean-up for the communities near Superfund sites. This situation has very detrimental effects when chemicals like

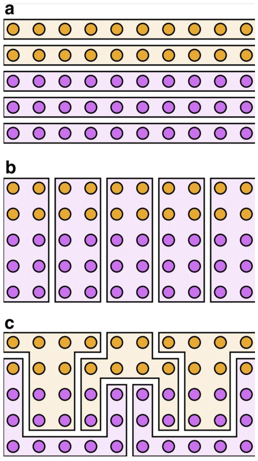



**Figure 2.** Gerrymandering Strategies a. Normal b. Cracking c. Packing [4]

2 lead pollute these communities and damage the physical development of children[5]. Without the political power to prevent toxic waste accidents and hazardous facilities, this creates an asymmetric distribution of wealth, where low-income marginalized communities accumulate worse risks. This situation reinforces and creates widespread health disparities that are long-term and not easily reversible, such as cancer[5].

The negative repercussions of gerrymandering are not only caused by this misrepresentation. It also distorts the representation given to constituents in a district[8]. Figure 3 shows evidence of packing black voters in VA.

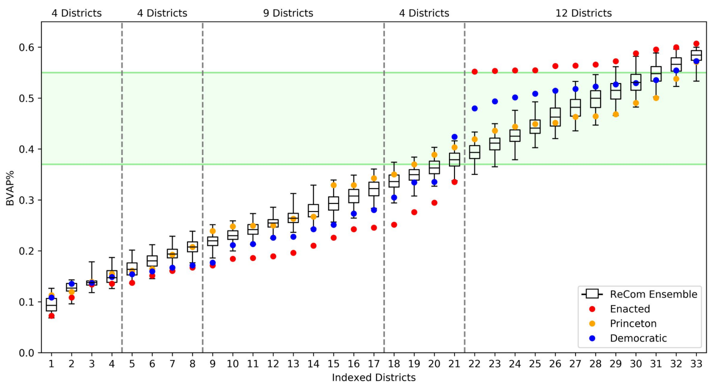
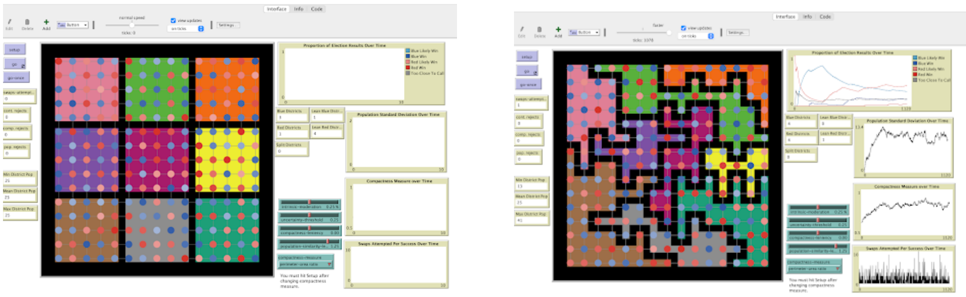



**Figure 3.** Black Voting Age Population [7]

Gerrymandering has been hard to measure and quantify over time, which worsens the problem because state lawmakers and courts have trouble applying a standard to gerrymandered districts even if they "know it when they see it"[1]. However, now there are many different measures and computational tools that are applied to maps of congressional districts to measure the increasing gerrymandering that has been taking place. The trend of districts being less "compact" on different measures has accelerated, especially after the introduction of more computing power and data in the 80s and 90s[1]. This trend is a strong indicator of gerrymandering because the different strategies involved in gerrymandering rely on selectively changing the districts to include specific demographics rather than creating a more natural "compact" district based on geographic features.



(a) Model after setup

(b) Model after running

**Figure 4.** Model after setup and after running

## 2. Methodology

### 2.1. The model

We adapted an existing model called NetDistrict[6], a Netlogo model which consists of 15 x 15 voter blocks (red/blue) and nine districts. The opacity of the blocks shows how strongly the block favors the political party. After setting up and running the model, the districts get gerrymandered and change boundaries according to the parameters set by the user. Figure 4 is a screenshot of the interface of the original NetDistrict model before and after running in one scenario.

The model contains the following parameters:

1. Intrinsic-moderation: The intrinsic moderation parameter controls how strongly the blocks favor their party. A lower intrinsic moderation causes all the voter blocks to only strongly support either party. A higher value increases the number of the leaning districts and indecision in voting[6].

2. Uncertainty-threshold: If a block's partisan score is below 0.5 by a margin greater than the uncertainty threshold, it is a red vote. If the partisan score is below 0.5 by a margin less than the uncertainty threshold, it is a lean-red vote. If the partisan score is above 0.5 by a margin greater than the uncertainty threshold, it is a blue vote. If the partisan score is above 0.5 by a margin lesser than the uncertainty threshold, it is a blue vote[6].
3. Compactness-leniency
4. Population-similarity-leniency
5. Compactness-measure: The options for compactness measures are perimeter-area ratio and mean path length. According to the creators of the model, "perimeter-area ratio is a measure of how much 'outside' a district has"[6]. It would flag efforts to include farther districts instead of closer ones, with ill intentions. Mean path length works similarly; long and artificial tendrils to districts results in a higher main path length[6].

We propose to make the following improvements/additions to the model:

1. Change the district shapes in the model to simulate Virginia voting districts.
2. Include reporters that keep track of the percentage of the red and blue blocks in the model. Also, include blue and red scores (normalized partisan scores).
3. Include a slider to change the partisan score odds of set up.
4. Include a drop-down menu to change the number of districts to 25.

## 2.2. Improving the model

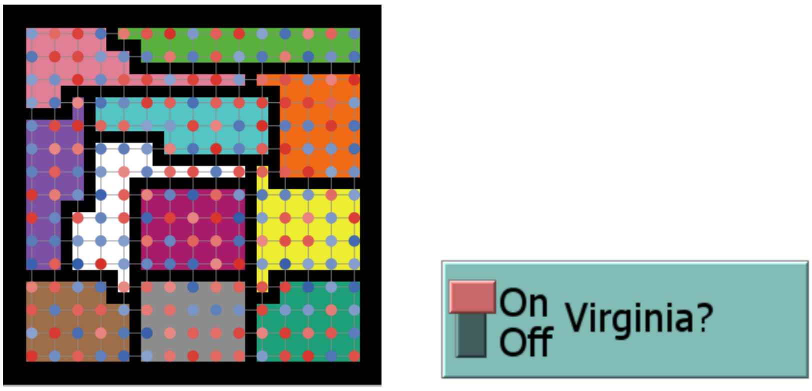
### 2.2.1. Step 1: Change the district shapes in the model to simulate Virginia

Using the map of Virginia's voting districts (Figure 1) as a reference, we included an option in the simulation to model Virginia's voting districts. While our model is not perfectly accurate, we took the following steps:

1. First, we divided the model into 11 districts.
2. Then we distributed the number of blocks among the districts depending on the actual population in Virginia's districts. Hence some districts have more or fewer blocks than others.
3. Finally, we changed the district shapes so that that districts which share boundaries on Virginia's map would share borders in ours as well.

We included a switch. If the user flips the switch to 'on' and sets up the model again, the model switches to 'Virginia mode.' We can see in Figure 1 that each Virginia congressional district has a number. In our model, yellow represents District 1, turquoise represents District 2, magenta represents District 3, grey represents District 4, white represents District 5, violet represents District 6, cyan represents District 7, orange represents District 8, brown represents District 9, pink represents District 10, and finally green represents District 11. The number of blocks in each district depends on the actual population in the districts.

Figure 5 shows screenshots of the model and the Virginia switch.




(a) Virginia model (b) Virginia switch

**Figure 5.** Virginia model and Virginia switch

#### 2.2.2. Step 2: Include reporters to show the number of red/blue blocks and red/blue scores

Our next step was writing code to display the number of blue/red blocks and the blue/red scores. We included two monitors which show the number of blue and red blocks; each block is either labeled red or blue, irrespective of how strong their inclination is towards the party. For example, if there is a light blue block (which only slightly leans to the blue party) and a dark blue block (which is in strong favor of the blue party), both would be counted as blue blocks.

We also included two monitors to display the "blue score" and "red score." The blue and red scores indicate the normalized partisan score. We obtained the partisan score of a block and adjusted it so that $Total\_Blue\_Score + Total\_Red\_Score = 1$. The difference between just displaying the number of blue and red blocks and the blue and red score is that the score of two blocks can be different even if they are of the same party.

Previously, we saw that a light blue block and a dark blue block would count as blue blocks. But their "blue score" would be different; the dark blue block would have a higher blue score because it is more in favor of the blue party. The same applies to the red scores. Hence the score is a more accurate representation of the "popular vote" among people because it considers how strongly or weakly the blocks favor the party. Figure 6 shows a screenshot of the four monitors.

#### 2.2.3. Step 3: Include a slider to change partisan score odds of set up

Our next step was introducing a slider to change the partisan score odds of set up. Doing so means that we would include an option to change the probability of a block

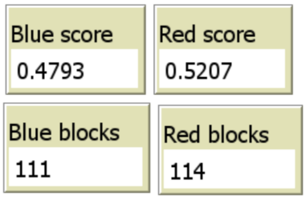



**Figure 6.** Monitors for Blue/Red score and number of blue/red blocks

6 being red or blue. The default setting only allows an equal chance for a block to be red or blue, to give both parties an equal and fair chance to win. The slider we introduced helps observe bias. It enables the user to change the odds to 55-45, 60-40, 52-48, and so on, according to the political climate.

We did this by accepting the slider input and using NetLogo's random keyword to include bias if needed. Including the slider means we cannot have a 50% chance for a block to be red or blue - the chance is arbitrary, depending on the user's selection. Assume there is $x\%$ support for the red party and $(100 - x)\%$ support for the blue party. We picked a random number $n$ between 1 and 100. If $1 <= n <= x$, we set that block to red. Else, we set it to blue. We used the same method for all 225 blocks. This slider gives the user more freedom to observe bias in politics. Figure 7 shows a screenshot of the partisan-odds slider.


**Figure 7.** Slider to adjust partisan odds

### 2.2.4. Step 4: Include a drop-down menu to change the number of districts to 9 or 25

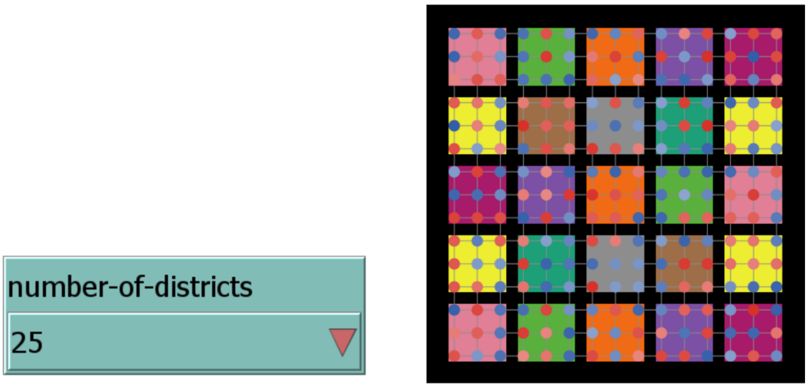
We included an additional feature in our model if the user wanted to check the outcomes for a larger number of districts. We included a drop-down menu that provided the user with the choice to have either 9 or 25 districts. The districts would still be of equal areas, and they would be square-shaped. Figure 8 shows screenshots of the drop-down menu to change the number of districts and the model with 25 districts.

## 2.3. Include a tick limit

We added code to stop the model after 2000 ticks since the original model ran forever. In the 'to go' function, we added

$$\text{if } ticks > 2000\ [stop]$$

If needed, the user can change this limit in the code.




(a) Drop-down menu to change number of districts

(b) Model with 25 districts

**Figure 8.** Drop-down menu and model with 25 districts

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## 3. Results

We have specified the abbreviations used in the observation tables in Table 1.

| | Abbreviation |
|---|---|
| Number of Blue districts after setup and before running | IB |
| Number of Leaning Blue districts after setup and before running | ILB |
| Number of Red districts after setup and before running | IR |
| Number of Leaning Red districts after setup and before running | ILR |
| Number of Split districts after setup and before running | IS |
| Number of Blue districts after 2000 ticks | FB |
| Number of Leaning Blue districts after 2000 ticks | FLB |
| Number of Red districts after 2000 ticks | FR |
| Number of Leaning Red districts after 2000 ticks | FLR |
| Number of Split districts after setup and before running | IS |
| Blue Score | BS |
| Red Score | RS |
| Number of Blue Blocks | BB |
| Number of Red Blocks | RB |
| Proportion of election results after 2000 ticks | Results |

**Table 1**

Legend for tables

## 3.1. Step 1 - Results after running in Virginia mode

**Parameters**
Virginia? switch: ON
intrinsic-moderation: 0.20% (default)
uncertainty-threshold: 0.00 (default)
compactness-leniency: 0.00 (default)
popularity-similarity-leniency: 0.00 (default)
compactness-measure: perimeter-area-ratio (default)
partisan-score-odds: 0.5 (default).

**The results are in Table 2.**
The number of leaning blue and leaning red districts was zero in all our runs, so we have not included this in the observation table.

| IB | IR | IS | FB | FR | FS | Results |
|---|---|---|---|---|---|---|
| 5 | 6 | 0 | 4 | 7 | 0 | Red win:0.4346, Blue win:0.3506, Too close to call:0.2148 |
| 8 | 2 | 1 | 7 | 2 | 2 | Blue win:0.992, Too close to call:0.008 |
| 4 | 7 | 0 | 3 | 7 | 1 | Red win:0.9496, Too close to call:0.0435, Blue win:0.007 |
| 4 | 6 | 1 | 3 | 7 | 1 | Red win:0.8686, Too close to call:0.0854, Blue win:0.046 |
| 5 | 6 | 0 | 5 | 5 | 1 | Blue win:0.7717, Too close to call:0.1164, Red win:0.1119 |
| 5 | 6 | 0 | 4 | 6 | 1 | Red win:0.978, Blue win: 0.045, Too close to call:0.0175 |
| 3 | 8 | 0 | 4 | 7 | 0 | Red win:1.0 |
| 3 | 8 | 0 | 4 | 7 | 0 | Red win:0.8961, Too close to call:0.0579, Blue win:0.046 |
| 4 | 7 | 0 | 4 | 5 | 2 | Red win:0.7168, Blue win: 0.1563, Too close to call:0.1269 |
| 5 | 5 | 1 | 5 | 6 | 0 | Blue win:0.52, Red win: 0.2892, Too close to call:0.1908 |

**Table 2**
Results after running the model in Virginia mode

## 3.2. Step 2 - Results after including monitors for red/blue blocks and scores

**Parameters**
Virginia? switch: OFF (default)
intrinsic-moderation: 0.20% (default)
uncertainty-threshold: 0.00 (default)
compactness-leniency: 0.00 (default)
popularity-similarity-leniency: 0.00 (default)
compactness-measure: perimeter-area-ratio (default)
partisan-score-odds: 0.5 (default) number-of-districts: 9 (default)

There are four new monitors now - number of red blocks, number of blue blocks, blue score, and red score.

9 **The results are in Table 3.**
The number of leaning blue and leaning red districts was zero in all the runs, so they are not included in this observation table.

| IB | IR | IS | BS | RS | BB | RB | Results |
|---|---|---|---|---|---|---|---|
| 6 | 3 | 0 | 0.4776 | 0.5224 | 106 | 119 | Red win 0.8, Too close to call 0.131, Blue win 0.069 |
| 4 | 4 | 1 | 0.4974 | 0.5026 | 112 | 113 | Red win 0.579, Blue win 0.221, Too close to call 0.2 |
| 3 | 4 | 2 | 0.4705 | 0.5295 | 108 | 117 | Red win 0.841, Too close to call 0.097, Blue win 0.048 |
| 4 | 5 | 0 | 0.4825 | 0.5175 | 109 | 116 | Red win 0.593, Too close to call 0.228, Blue win 0.179 |
| 5 | 3 | 1 | 0.5335 | 0.4665 | 118 | 107 | Blue win 0.931, Too close to call 0.041, Red win 0.028 |
| 5 | 3 | 1 | 0.5553 | 0.4447 | 126 | 99 | Blue win 1.0 |
| 4 | 4 | 1 | 0.4947 | 0.5053 | 114 | 111 | Blue win 0.524, Too close to call 0.262, Red win 0.228 |
| 3 | 5 | 1 | 0.4707 | 0.5293 | 108 | 117 | Red win 0.883, Too close to call 0.09, Blue win 0.028 |
| 3 | 3 | 3 | 0.524 | 0.476 | 116 | 109 | Blue win 0.745, Too close to call 0.124, Red win 0.124 |
| 5 | 2 | 2 | 0.533 | 0.467 | 117 | 108 | Blue win 0.731, Too close to call 0.138, Red win 0.124 |

**Table 3**

Results when probability of a block being red or blue is 50%, with red/blue districts and red/blue scores

### 3.3. Step 3 - Results after including a slider to change partisan score odds

**Parameters**
Virginia? switch: OFF (default)
intrinsic-moderation: 0.20% (default)
uncertainty-threshold: 0.00 (default)
compactness-leniency: 0.00 (default)
popularity-similarity-leniency: 0.00 (default)
compactness-measure: perimeter-area-ratio (default)
partisan-score-odds: CHANGED TO 0.4, 0.45, 0.48, 0.52, 0.55, 0.6.
number-of-districts: 9 (default)

We ran the model 10 times **each** with different partisan odds and averaged the results. **The results are in Table 4.**
The number of leaning blue and red districts and split districts were zero in all the runs. So we have not included this in the observation table.

### 3.4. Step 4 - Results after changing number of districts to 25

**Parameters**
Virginia? switch: OFF (default)
intrinsic-moderation: 0.20% (default)
uncertainty-threshold: 0.00 (default)
compactness-leniency: 0.00 (default)
popularity-similarity-leniency: 0.00 (default)
compactness-measure: perimeter-area-ratio (default)

| Partisan<br>Odds<br>Red-Blue | Mean<br>IB | Mean<br>IR | Mean<br>BS | Mean<br>RS | Mean<br>BB | Mean<br>RB | Results |
|---|---|---|---|---|---|---|---|
| 40-60<br>Red - 0.4<br>Blue - 0.6 | 7.5 | 1.5 | 0.60256 | 0.39744 | 135.8 | 89.2 | Blue win 0.9995<br>Too close to call 0.00035<br>Red win 0.00015 |
| 45-55<br>Red - 0.45<br>Blue - 0.55 | 6.3 | 2.7 | 0.55286 | 0.44714 | 124.7 | 100.3 | Blue win 0.945082<br>Too close to call 0.0367<br>Red win 0.02298 |
| 48-52<br>Red - 0.48<br>Blue - 0.52 | 4.5 | 4.5 | 0.51499 | 0.48501 | 115.7 | 109.3 | Blue win 0.54416<br>Red win 0.35914<br>Too close to call 0.09671 |
| 52-48<br>Red - 0.52<br>Blue - 0.48 | 3.3 | 5.7 | 0.46934 | 0.53066 | 111.4 | 113.6 | Red win 0.7555<br>Blue win 0.19481<br>Too close to call 0.0497 |
| 55-45<br>Red - 0.55<br>Blue - 0.45 | 1.8 | 7.2 | 0.42437 | 0.57563 | 95.2 | 129.8 | Red win 0.95025<br>Too close to call 0.02917<br>Blue win 0.02058 |
| 60-40<br>Red - 0.6<br>Blue - 0.4 | 1.4 | 7.6 | 0.39757 | 0.60243 | 89.6 | 135.4.8 | Red win 0.99306<br>Too close to call 0.00495<br>Blue win 0.002 |

**Table 4**

Average of 10 observations each with different partisan odds

10 partisan-score-odds: 0.5 (default).
number-of-districts: 25

**The results are in Table 5.**
The number of leaning blue, leaning red districts and the initial number of split districts was zero in all the runs, so we have not included this in the observation table.

| IB | IR | FB | FR | FS | Results |
|---|---|---|---|---|---|
| 13 | 12 | 11 | 11 | 3 | Blue win:0.674, Red win:0.178, Too close to call:0.155 |
| 13 | 12 | 15 | 9 | 1 | Blue win:0.736, Red win:0.14, Too close to call:0.124 |
| 11 | 14 | 9 | 13 | 3 | Red win:0.953, Too close to call:0.047 |
| 12 | 13 | 9 | 10 | 6 | Red win:0.729, Blue win:0.155, Too close to call:0.124 |
| 5 | 20 | 7 | 16 | 2 | Red win:1.0 |
| 15 | 10 | 1 | 11 | 3 | Blue win:0.736, Red win:0.14, Too close to call:0.14 |
| 15 | 10 | 10 | 7 | 8 | Blue win:0.806, Red win:0.109, Too close to call:0.093 |
| 15 | 10 | 14 | 10 | 1 | Blue win:0.86, Red win:0.093, Too close to call:0.054 |

**Table 5**

Results when number of districts is 25

## 4. Discussion

### 4.1. Step 1 - After running the model in Virginia mode

We notice a trend in all the cases - different parties win through time, which heavily depends on the initial number of blue and red districts. But after a certain number of ticks (which varies from one run to another), one party becomes the clear winner for a very long time. This situation arises when the state becomes a "blue" or "red" state. After a point in time, the outcomes are predictable, and one party always wins the majority afterward. Until that point in time, we could consider the state a "swing" state because the results keep changing, and we cannot easily predict who will win. But after a threshold (which is affected by the initial odds), one party stays the clear winner.

Our Virginia model could be used to model the Virginia elections to predict winners. The model can be improved in the future by allowing certain districts to have more blue or red blocks, depending on the actual political stances in each district in Virginia. "Blue" areas in VA could have more blue blocks, and "red" areas in VA could have more red blocks. In this model, the distribution of blue and red is just random, and it has nothing to do with the actual political climate.

### 4.2. Step 2 - After including monitors to display red/blue scores and blocks

From the monitors, we can see the initial number of blocks and the normalized scores after setup. These values do not change while running the model because the blocks do not change colors - only the district boundaries change.

From Table 3, we can see that the election results heavily tend to favor the party, which has a higher initial number of blocks/score. The initial setup has a high effect on the final result. However, in certain cases, even when the partisan odds are equal (50% probability that a block will be red or blue), the bias in the outcome is sometimes very high. For example, in one case, blue wins all the time even though the scores only differed by around 0.1 (blue score was 0.5553 and the red score was 0.4447). Hence, the initial scores have a massive effect on the final result. When the difference in scores is higher, the outcome tends to bias more. We can see that "too close to call" is the second-most prevalent result when the partisan odds are 50% because there is a 50-50 chance for a particular party to win. The first most-prevalent result would be a particular party winning, and the second-most tends to be "too close to call."

In one interesting case, the total red score was higher than the total blue score. But the blue party still won the most through time, showing that the popular vote is not all that matters. This situation is similar to the 2016 Clinton versus Trump elections. Although Clinton had the popular vote (higher vote count), she lost the electoral vote. This situation has happened in this case, where there are more people in support of red, but blue still ended up winning the most through time. The electoral vote is what matters above the popular vote in US politics.

### 4.3. Step 3 - After including sliders to change partisan score odds

From Table 4, we can see that biasing the initial partisan score greatly affects the results. As we increase the odds of a block being red there is an increase in the number of red districts, red blocks, and red score. And vice versa - if we increase the odds of a block being blue, the number of blue districts, blue blocks, and blue increases. The proportion of elections won by a party also increases when the odds are increased in favor of the party. In Table 4, we can see that as the odds of a block being red is increased, the proportion of elections won by blue decreases, and the proportion of elections won by red increases. These observations show that if the USA had a higher bias in the percentage of red and blue supporters, the party with fewer supporters would mostly never stand a chance. Hence an equal balance is required for democracy, or else one party would mostly win through time. This slider can help model real-world scenarios. What if one year, there was a 52% support for the blue party and 48% support for the red party? Our slider expands on this and increases the model's capability.

### 4.4. Step 4 - After changing the number of districts to 25

This feature is an additional feature we added if the user wanted to check outcomes for a large number of districts. There is a difference when we ran the model with 25 districts in comparison to 9 districts. When we had nine districts, the second most probable outcome would mostly be "too close to call." But in the case of 25 districts, the second most probable outcome was mostly the opposite party winning. This situation occurs because we now have more districts, so the chance for the opposite party to win would also be higher. Another interesting observation is that the initial number of split districts (after setup and before running) was always zero. After 2000 ticks, there would be some split districts, but initially, there are no split districts in the runs we had.

### 4.5. Does making districts less compact increase gerrymandering in the model?

As will be discussed further, there are many limitations to this model. One thing we found was that the average number of districts a party wins by does not increase much over time. As noted in the discussion, most model runs end with one party a clear winner, but from the initial state, the increase is not very large as BehaviorSpace trials showed. An issue may be that the model's algorithm only uses compactness as a measure and does not maximize votes themselves. However, compactness can still generate gerrymandered outcomes, and more importantly, give a conceptual understanding needed to build non-gerrymandered districts. Figure 9 shows the average gap in vote outcomes over time.

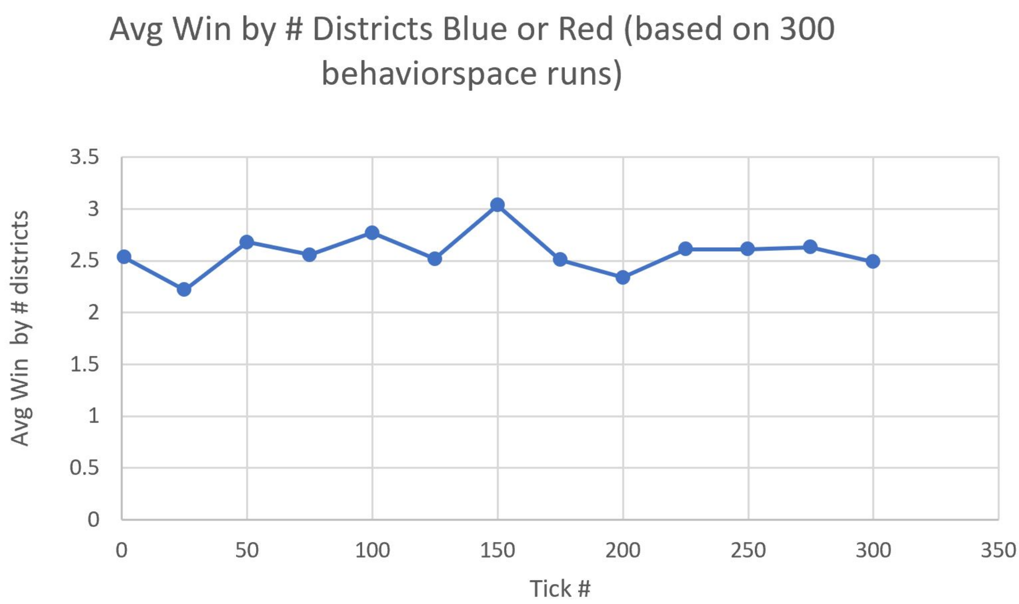


**Figure 9.** Average Win by  Districts Blue or Red based on 300 BehaviorSpace runs (and 300 tick limit)

### 4.6. Limitations of the model

1. The whole environment is a two-dimensional square that does not wrap around. For future research, we can implement a wrap-around environment to implement a torus-shaped environment which could yield interesting results.
2. For future research on modeling Virginia, the environment can be modeled in a way that it is shaped exactly like VA, with the districts accurately modeling the boundaries and population density.
3. The compactness measure is arbitrary, and the model does not pack or crack voters well.
4. Our model is not easy to validate against real-world data. This model is mostly just a conceptual tool that can model possible scenarios, but it can be valuable.
5. There is no change in demographics over time. We can see this lack of change in the two outcomes after running the model: a group wins every election, or a group wins the first few elections and then loses the rest. This behavior has a threshold around the number of blocks being roughly equal.

## 5. Further Work and Conclusion

Because this model is so simplified and is currently only useful as a *conceptual* model, there is much room for improvement. However, work has shown the potential use of computational simulation in redistricting[3]. Most of the simulations focus on using the precinct-level data as building blocks to create more compact districts. The approach of generating unfair districts with a simulation of voting seems novel. The model could be expanded to be based on real precinct-level data, and then instead of maximizing the compactness score, it could minimize it. It also seems that the shortest mean path length measure has not been used before. Other extensions could include altering the program so that the partisan demographics change over time. Creating a more realistic simulation would require modifying the grid and blocks to be accurate based on size and distance.

Also, based on our experience in modifying the districts, we could set some districts up so that they could not swap with other districts. Doing so could be useful, because in some cases, the simulated possible districts do not meet legal criteria that have been established. In Florida, for example, courts decided the 5th district is required to not violate the Voting Acts Right. Many computational simulations would never generate the fifth district, but this alteration would work around this requirement.

In conclusion, the results of the elections heavily depend on the initial setup. Our improvements to the model expand on the original model's capabilities. Gerrymandering is a severe issue with drastic long-term consequences; modeling it could help observe this issue and how to prevent it.

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## Affiliations

**Luke Palmieri**
George Mason University, Virginia. lpalmie@masonlive.gmu.edu

**Gowri Prathap**
George Mason University, Virginia. gprathap@gmu.edu