Impacts of Differential Privacy on Fostering more Racially and Ethnically Diverse Elementary Schools

Keywords: Education, Inequality, Socioeconomic Diversity, Differential Privacy, Optimization

Extended Abstract

In the face of increasingly severe privacy threats in the era of data and AI, the US Census Bureau has recently adopted differential privacy [1], the *de facto* standard of privacy protection for the 2020 Census release. Enforcing differential privacy involves adding carefully calibrated random noise to sensitive demographic information prior to its release. This change has the potential to impact policy decisions like political redistricting and other high-stakes practices [3, 4], partly because tremendous federal funds and resources are allocated according to datasets (like Census data) released by the US government. One under-explored yet important application of such data is the redrawing of school attendance boundaries to foster less demographically segregated schools. The purpose of this study is to explore how differential privacy might impact diversity-promoting boundaries in terms of the following outcome measures: changes in segregation, estimated travel times, and school switching.

Data and methods. We focus on elementary schools across 67 school districts in Georgia, using the datasets presented in [2]: 2021-2022 elementary school attendance boundaries, 2019-2020 publicly-available school attendance data by race/ethnicity (White, Black, Asian, Native, and Hispanic/Latinx), and 2020 Census-level estimates of the number of non-adults per demographic group living in each Census block. We use both the school and Census data to estimate the number of students per demographic group who live in each block and attend each school (based on current attendance boundaries). We study the constraint programming model from [2], which uses this demographic information ($\boldsymbol{N}$) to reallocate Census blocks to schools in order to minimize White/non-White *dissimilarity* , i.e., $\left(\sum_{s\in S} |N_{w,s}/N_w - N_{nw,s}/N_{nw}|\right)/2$. Here, s represents a school in the set of district elementary schools S; N_{nw} and $N_{nw,s}$ are the district-wide and school s-specific counts of non-White students (with N_w and $N_{w,s}$ defined analogously for White students). Additional constraints include capping increases in students' travel times and increases in school sizes, and contiguity. The model solution is referred to as the *non-private (school) assignment*.

From the perspective of data privacy, $\boldsymbol{N}$ is usually considered sensitive information and requires privacy protection. The common practice of *differential privacy* is to mask the entries of $\boldsymbol{N}$ with random noise added. This work employs a variant of the Laplace mechanism [1] to ensure ε-differential privacy, i.e., $\tilde{\boldsymbol{N}} = (\boldsymbol{N} + \lfloor \boldsymbol{\eta} \rceil)_+$, where each entry of $\boldsymbol{\eta}$ follows an i.i.d. Laplace distribution $\mathrm{Lap}(2/\varepsilon)$ while the two operations, $\lfloor \cdot \rceil$ and $(\cdot)_+$, are used to restore integrity and non-negativity. Small ε values usually require large noise and thus imply strong privacy guarantees. We call the boundary redrawing resulting from the obfuscated data $\tilde{\boldsymbol{N}}$ the *private (school) assignment*. Due to random nature of $\tilde{\boldsymbol{N}}$, we simulate 100 independent rezonings for each district and privacy budget $\varepsilon \in \{2, 4\}$. Figure 1 shows an overview of the datasets, constraints, and data obfuscation.

Results. Focusing on $\varepsilon = 2$, Figure 3 shows that the private assignment would result in more racially segregated attendance boundaries across the studied districts than the non-private one: a median decrease of 15.23%, versus a median 23.51% reduction under non-private assignment. This may be due in part to the fact that the private assignment assigns (around 5%) fewer census blocks to different schools than the non-private one. Figure 4 shows that just over half of the reassignments of Census blocks made by the private assignment coincide with those made by the non-private one. Figure 5 visualizes the changes in travel time resulting from different assignments. Interestingly, both private and non-private boundary changes do not substantially change travel times, and in many cases, reduce them across demographic groups. Figure 6 shows that fewer students would be reassigned to other schools by the private assignment, compared with the non-private one, and the reduction is similar across different demographic groups. An exception occurs under private assignment with $\varepsilon = 4$, where more Native American students are affected, likely due to their small population size.

Next, we hone into specific configurations across districts—namely, the scenario in each district that would produce the smallest reduction in segregation due to introduction of differential privacy (i.e., the largest difference in dissimilarity index between the private and non-private assignments). We use linear regression to study which school district features are associated with this value. Results are summarized in Table 1. We find that out of the included variables, only the district's baseline White/non-White dissimilarity (D_{curr}) is significantly predictive of this difference: the higher D_{curr}, the less diverse the private assignment is. The adjusted R^2 of the model is also generally small (less than 0.35). Together, these values suggest that the impact of differential privacy on potential school integration is likely to vary widely across districts, and will be influenced by district-level idiosyncrasies like current boundaries, demographic distributions across constituent neighborhoods, and other factors not included in our model.

Discussion. Overall, our results demonstrate that private assignment reassigns fewer students and yields less diverse attendance boundaries. Furthermore, only a small amount of the difference between private and non-private assignment's impact on changes in diversity are explained by district-level demographics, suggesting the nuances of each district's current boundaries and population distribution are likely to influence how much applications of privacy affect redistricting. These findings point to a privacy-diversity tradeoff local educational policymakers may face in forthcoming years, particularly as computational methods increasingly play a role in attendance boundary redrawing. Interestingly, adding differential privacy does not exert large disparate impacts on travel time and percents of the students rezoned across different groups. An important limitation of this work is that it focuses on the "average-case" analysis across multiple districts. District-level nuances (along with different privacy budgets) may impact how much additions of privacy impact school assignment policies in practice.

References

[1] C. Dwork, F. McSherry, K. Nissim, and A. Smith. Calibrating noise to sensitivity in private data analysis. In *Theory of Cryptography: Third Theory of Cryptography Conference, TCC*, pages 265–284, 2006.

[2] N. Gillani, D. Beeferman, C. Vega-Pourheydarian, C. Overney, P. Van Hentenryck, and D. Roy. Redrawing attendance boundaries to promote racial and ethnic diversity in elementary schools. *Revise and resubmit*, 2022.

[3] C. T. Kenny, S. Kuriwaki, C. McCartan, E. T. Rosenman, T. Simko, and K. Imai. The use of differential privacy for census data and its impact on redistricting: The case of the 2020 us census. *Science advances*, 7(41):eabk3283, 2021.

[4] R. Steed, T. Liu, Z. S. Wu, and A. Acquisti. Policy impacts of statistical uncertainty and privacy. *Science*, 377(6609):928–931, 2022.

Features	Coefficients	Standard Error	t	p-value	95% Confidence Interval	
% White	0.0099	0.006	1.699	0.095	-0.002	0.022
% Black	0.0083	0.006	1.503	0.138	-0.003	0.019
% Asian	0.0007	0.001	0.666	0.508	-0.001	0.003
% Native	0.0006	0	1.241	0.22	0	0.001
% Hispanic	0.0042	0.003	1.327	0.19	-0.002	0.011
# Students	0.0014	0.002	0.824	0.414	-0.002	0.005
# Schools	-0.0011	0.002	-0.634	0.529	-0.005	0.002
$\mathbb{1}\{\text{rural}\}$	-8.23E-05	0	-0.281	0.78	-0.001	0.001
$\mathbb{1}\{\text{smallcity}\}$	-0.0001	0	-0.583	0.562	-0.001	0
$\mathbb{1}\{\text{suburban}\}$	0.0002	0	0.566	0.573	0	0.001
$\mathbb{1}\{\text{urban}\}$	0.0002	0	0.572	0.57	-0.001	0.001
D_{curr}	0.0014	0	3.135	0.003	0.001	0.002

Table 1: Regression result. D_{curr} is a shorthand for the dissimilarity index associated with the current assignment and the last two columns represent the lower and upper bounds of the 95% confidence intervals.

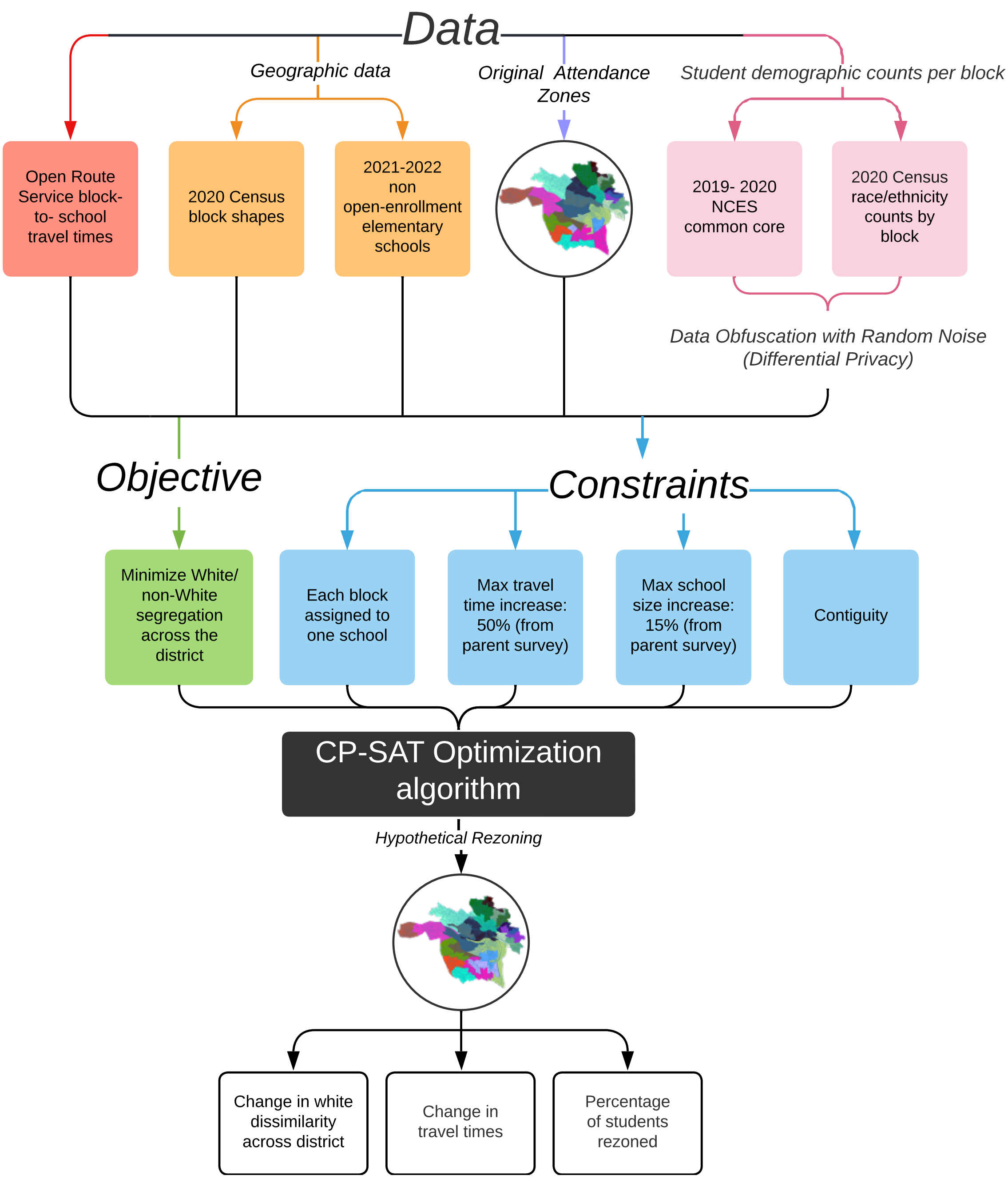

Figure 1: Input data, objective function, constraints, and outcome measures from the optimization model [2]. Note that, in order to retrieve the private assignment, the demographic data of students should be injected with random noise prior to optimization.

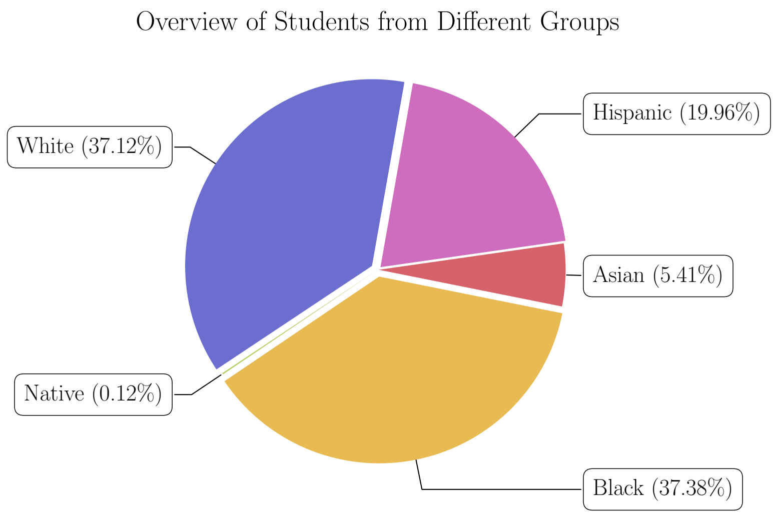

Figure 2: Demographic composition of students attending schools from the 67 districts in Georgia.

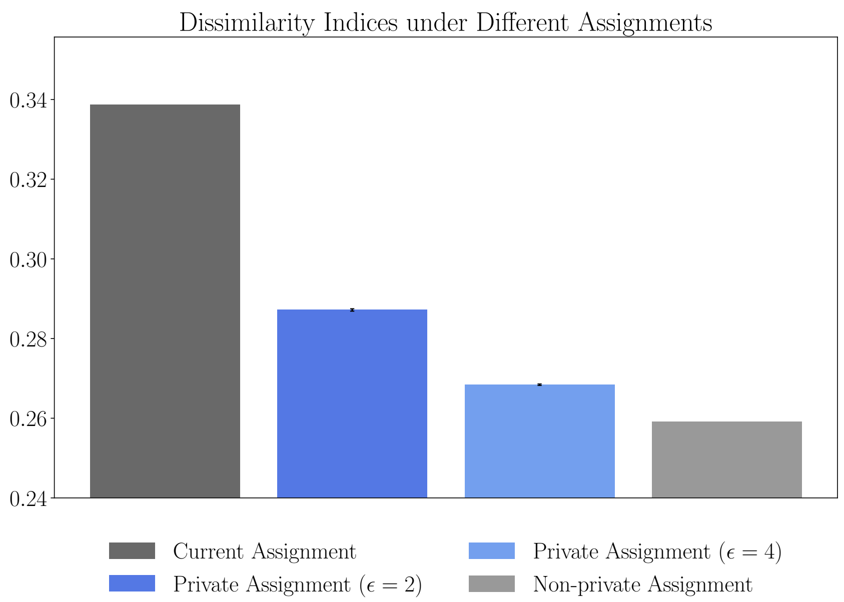

Figure 3: Dissimilarity indices associated with current, non-private, and private assignments with privacy budget $\varepsilon \in \{2,4\}$. Error bars depict 95% bootstrapped confidence intervals.

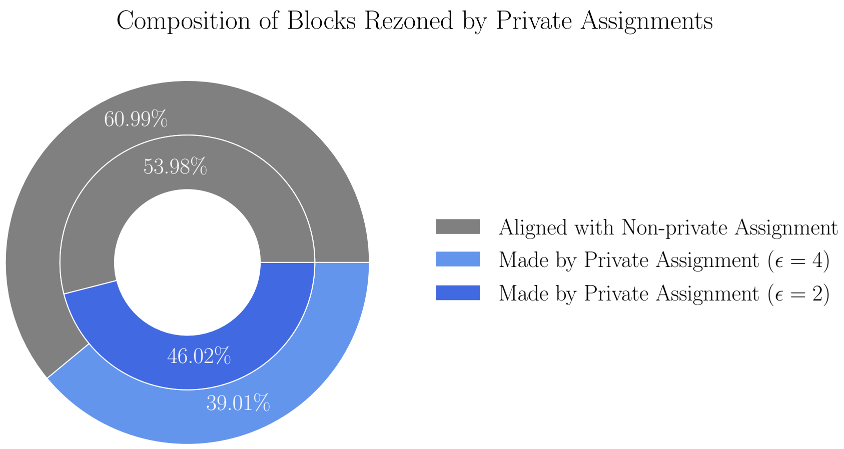

Figure 4: Composition of census blocks rezoned by private assignments. The inner and outer circles are correspondent to the private assignments with $\varepsilon = 2$ and 4 respectively.

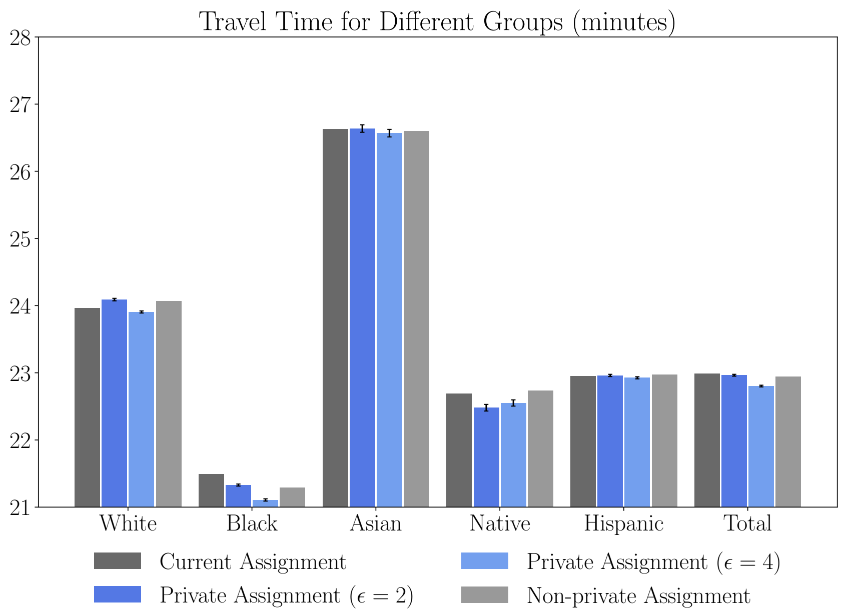

Figure 5: Travel time for different groups. Error bars depict 95% bootstrapped confidence intervals.

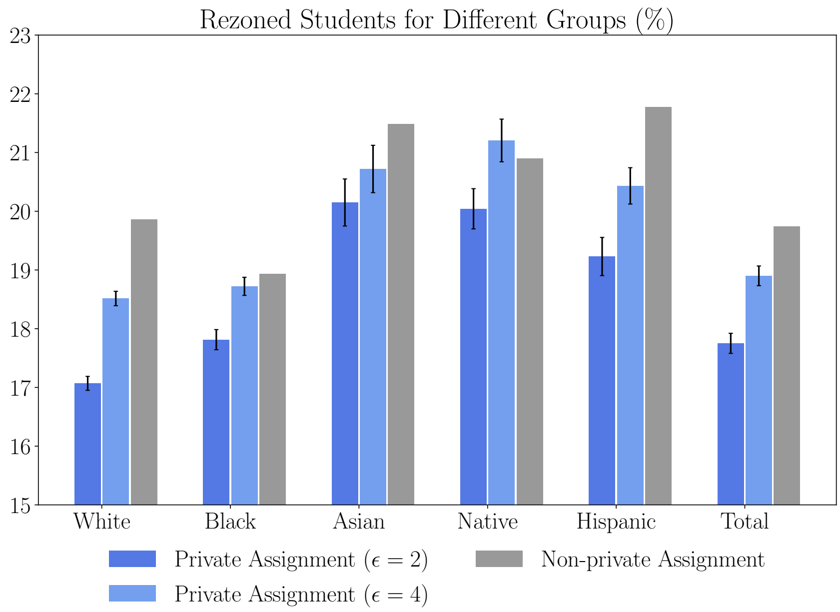

Figure 6: Percents of the students rezoned across different groups. Error bars depict 95% bootstrapped confidence intervals.