An improved BISG for inferring race from surname and geolocation

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Abstract

Bayesian Improved Surname Geocoding (BISG) is a ubiquitous tool for predicting race and ethnicity using an individual's geolocation and surname. Here we demonstrate that statistical dependence of surname and geolocation within racial/ethnic categories in the United States results in biases for minority subpopulations, and we introduce a raking-based improvement. Our method augments the data used by BISG—distributions of race by geolocation and race by surname—with the distribution of surname by geolocation obtained from state voter files. We validate our algorithm on state voter registration lists that contain self-identified race/ethnicity.

1. Introduction

Accurately measuring racial bias or "unfairness" in algorithms and systems is critical in many domains including machine learning, election law, data-driven predictions, lending practices, and healthcare coverage. However, a challenge to assessing and addressing racial disparities arises due to the absence of complete or reliable race and ethnicity information in many of these applications. To overcome this limitation, researchers and practitioners often use proxy methods that fill in, or impute, the missing data, allowing for racial disparities to be identified more effectively.

Bayesian Improved Surname Geocoding (BISG) is a widely used algorithm for race/ethnicity imputation [25] that gives a probabilistic estimate of race/ethnicity for an individual in the United States using surname and geolocation (often census tract or block group). BISG has been used to measure racial disparities across a range of applications in government, academia, and industry including health care [25, 30], lending practices [17], voting patterns [27], user experience in social media [4], and many other areas [24, 33, 46]. For example, the U.S. Department of Justice and the Consumer Finance Protection Bureau entered into a $98 million settlement with Ally Financial for racially-biased lending, based in part on BISG [16]. Meta announced the launch of a BISG-based algorithm for reducing racial bias in advertisement delivery as part of a recent settlement with the Departments of Justice and Housing and Urban Development [44]. Recently, BISG was used to infer race/ethnicity of voters in federal voting rights cases, and the use of BISG was subsequently upheld in the U.S. Court of Appeals [1, 2, 9, 20].

BISG has become popular because it uses publicly available census data and is mathematically straightforward. However, BISG relies on a crucial assumption—that, within the U.S. population, surname and geolocation are conditionally independent of race. This means that if we know a person's race, then their geolocation tells us nothing about their surname, and likewise, their surname gives no information about their geolocation. While this assumption may be mathematically and practically convenient, it appears to contradict the conventional wisdom that people tend to live in close proximity to their relatives and others with similar demographic features.[1] For example, Korean surnames are prevalent in Fort Lee, New Jersey, while across the river in Manhattan, Asian surnames are much more likely to be Chinese.

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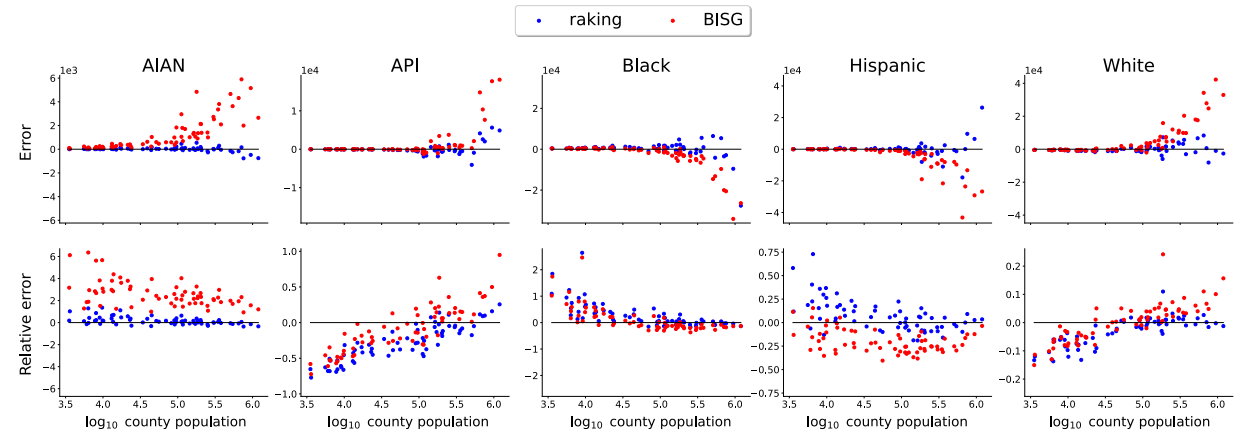
[1]These and other likely sources of inaccuracy in BISG's conditional independence assumption are noted in [35, 36].



	AIAN	API	Black	Hispanic	White
% of state:	0.4%	2.8%	14.1%	19.0%	63.6%
Rake % of state:	0.4%	2.8%	14.1%	19.0%	63.6%
BISG % of state:	1.1%	3.5%	12.3%	16.3%	66.7%
Rake Mean Error:	0%	0%	0%	0%	0%
BISG Mean Error:	207%	27%	-13%	-14%	5%
Rake Mean Abs. Error:	17%	14%	7%	6%	2%
BISG Mean Abs. Error:	207%	31%	14%	14%	5%

Figure 1: *Errors in subpopulation estimation for subsampled registered voters in each county in Florida in 2020 for two methods, BISG and raking. Each dot in the scatterplots represents error in one county with BISG or raking. Dots above the horizontal line correspond to overestimating the size of a subpopulation size in one county. Dots below the horizontal line indicate underestimating.*

Here, we demonstrate that dependence of surname and geolocation within racial/ethnic groups results in systematic inaccuracies in BISG, and we introduce a method for improving the predictions. We analyze the impact of BISG's independence assumption using voter registration lists in Florida and North Carolina, two of a handful of U.S. states that provide labeled race/ethnicity information on registered voters. Using state voter files, we construct a fully self-consistent BISG with exact factors and validate its accuracy on the full population on which it is trained. We demonstrate empirically that BISG consistently suffers from poor relative accuracy for small subpopulations. Furthermore, within subpopulations, the sign of the errors is consistent. For example, in Florida BISG underestimated the size of Hispanic subpopulations in 88% of counties and in nearly 50% of counties, Hispanic subpopulations were underestimated by at least 25% (see Figure 3). Similarly, the size of Asian and Pacific Islander (API) subpopulations was underestimated in 90% of counties and in 40% of counties, API subpopulations were underestimated by at least 25%. We provide extensive results of this study in Appendix A.

The prediction method we introduce is straightforward to implement, easily interpretable, and is more accurate and better calibrated than BISG. Our algorithm uses the inputs to BISG (joint distributions of race by geolocation and race by surname) in combination with two new data sources—the joint distribution of surname and geolocation obtained from state voter registration lists and the statewide race/ethnicity distribution of registered voters from the Voter Supplement of the Current Population Survey (CPS). Our predictions can be computed by first evaluating BISG predictions for all registered voters in a state and then modifying those predictions so that they coincide with known margins. This procedure is done via raking [22], a classical and widely used algorithm for fitting observed data to known margins. Summing our predictions over all surnames and geolocations in a given state gives a race/ethnicity distribution that matches the distribution estimated by the CPS. Similarly, our predictions' surname-by-geolocation two-way

margin (summing over race/ethnicity) matches the margins of state voter registration lists. The accuracy of our raking predictions depends on the accuracy and consistency of the margins that we rake to. These margins that have been widely used and studied in political science literature including their consistency and accuracy [28, 42, 5, 26].

If one were to sum BISG estimates over everyone in a particular state, the race/ethnicity estimate for that state would not match the true distribution. This may come as surprise, given that this information can be obtained from the race by geolocation inputs into BISG. However, without the joint distribution of surname and geolocation, BISG has no mechanism to enforce the accuracy of the statewide race/ethnicity margin. In the states we have tested, BISG's statewide race/ethnicity margins are often inaccurate, and county-level errors are frequently larger (see, e.g., Figure 1). A main advantage of our approach is that we use the joint distribution of surname and geolocation in state voter files to ensure that statewide margins of our estimates are accurate, at least up to the accuracy of state voter files and the Current Population Survey, two widely used and studied data sets.

Much of the literature on BISG focuses on error in measuring racial disparity on some outcome of interest. That is, the goal is to measure the race/ethnicity distribution by, for instance, political party, for a group of people with unknown race/ethnicity. Often, BISG is used to impute race/ethnicity of those people, and standard methods, or recently introduced alternatives such as [38, 41], are subsequently used to estimate racial disparities.[2] The accuracy of these racial disparity estimates combines various sources of error, including BISG error, correlation of BISG error with the outcome of interest, and the assumptions of the method used for disparity analysis [41]. There is a vast range of downstream applications of BISG to racial disparity measurement, and notions of errors in those applications [11, 17, 4, 25, 24, 33, 46]. We focus on classes of errors that are likely to impact many applications, albeit possibly in different ways for different applications. Our method and BISG are algorithms for estimating the joint distribution of race/ethnicity, surname, and geolocation and we use a variety of metrics to compare BISG and our method to the true joint distribution of race/ethnicity, surname, and geolocation. The subpopulation errors we report—estimated race/ethnicity of registered voters in various geographic regions (see, e.g., Figures 1, 2, and 9)—are also of applied interest in electoral politics, election law, and political science [21, 9, 1, 2, 32, 10].

We estimate race/ethnicity distributions of registered voters in Florida and North Carolina and report individual-level and mean errors across geographic regions. We use two methods to calibrate our test set (registered voters with labeled race/ethnicity) to the CPS margin: (i) subsampling the test set to match the CPS race/ethnicity distribution and (ii) transforming predictions from the voter file population to the CPS-implied population.

Our raking algorithm outperforms BISG across a range of metrics and both calibration approaches. For example, for the subsampled voter file, the mean absolute error of raking predictions in Florida in 2020 is 4% compared to 10% for BISG. In North Carolina, raking mean absolute error is 3% compared to 7% for BISG in 2020 and 3% for raking versus 5% for BISG in 2010. In Figure 1, we plot the accuracy of estimates of subpopulation size implied by BISG and raking in all counties in Florida in 2020. Figures 2 and 9 include the same results for North Carolina in 2020 and 2010 respectively.

Figures 1, 2, and 9 illustrate that mean errors of BISG are often large and correlated with county population.[3] For example, in Florida in 2020, BISG overestimates the size of API subpopulations

[2] In many applications, even when mean errors in BISG are negligible over the population of interest, standard methods for disparity analysis are biased. In particular, when BISG errors are correlated with an outcome of interest, bias is introduced in disparity estimates [14]. Techniques such as [41, 38] address these biases.

[3] Similarly, errors are also correlated with subpopulation size. For example, Hispanics are consistently undercounted

by over 25% while American Indian and Alaskan Native (AIAN) subpopulations are overestimated by over 100%. Our raking predictions, by design, recover the exact size of each subpopulation over the state. However, the errors of our method are also correlated with county population size.

In addition to validating our method and BISG in Florida and North Carolina, we implemented our prediction algorithm and BISG in several states without publicly available race/ethnicity information—New York, Ohio, Oklahoma, Vermont, and Washington. Our predictions and implementation for these states as well as Florida and North Carolina are publicly available.[4]

BISG was originally introduced for healthcare applications [25], and public health researchers have subsequently made methodological progress on race/ethnicity imputation. For example, Medicare BISG [40, 30] relaxes the independence assumption and uses logistic regression on demographic features to predict race/ethnicity. The public health family of methods and the applications they address are, from a statistical standpoint, distinct from research on BISG for registered voters or the general population. The primary difference is that in healthcare applications, practitioners often have access to large amounts of labeled data—data sets that include surname, geolocation, race/ethnicity, and other demographic data for a large percentage of the population of interest [25, 30]. Unfortunately there is no equivalent for the registered voter population outside of a few state voter registration lists. It is possible that methods like Medicare BISG can be applied to those voter registration lists, though we do not investigate that in this paper.

The central topics of this paper—a simple improvement on BISG and an analysis of BISG's errors—have been the subject of a wide literature. For example, failure modes of BISG are discussed in [14, 38, 8, 49, 29, 6] and race/ethnicity prediction algorithms include BISG-based methods [35, 36, 30] and many others [37, 45, 39]. This paper is distinct from those in two primary ways: (i) we introduce a simple and easily interpretable algorithm, which by itself is a major improvement on BISG and can also be combined with other race/ethnicity prediction algorithms, including several of the aforementioned ones, and (ii) we provide a novel approach to error analysis—isolating the impact of BISG's independence assumption by computing BISG predictions on a complete and self-contained data set with exact factors. We include a longer discussion of the relevant literature in Appendix F.

The remainder of this paper is organized as follows. Section 2 describes the raking-based prediction method that we propose. In Section 3, we present the results of validation of our method on predicting the race/ethnicity of registered voters in Florida and North Carolina. We discuss the results of our validation and directions for future work in Section 4. In the appendices, we first provide detailed results of our analysis of BISG on self-contained and complete data sets of registered voters (Appendix A). Appendix B details the BISG prediction that we use for the results in Section 3. In Appendix C, we describe an approach to validation of voter registration lists that uses a calibration map. Appendix D contains details on combining race/ethnicity classifications from the various data sets used in this analysis. Detailed results from validation on the accuracy and calibration of BISG and raking is contained in Appendix E, and Appendix F provides a literature review. .

in counties with small Hispanic populations in Florida in 2020. There are many features strongly correlated with county population in Florida and North Carolina and thus many features correlated with BISG errors in those states. We do not investigate those correlations in this paper. Recent work has shown that BISG errors are correlated with various socioeconomic and demographic factors [6].

[4] `https://github.com/pgree/raking_bisg`

2. Methods

In this section, we propose an algorithm for predicting race/ethnicity that uses raking (see, e.g., [22]) in combination with survey data and state voter files to improve BISG predictions.

We use the conventions and notation of log-linear modeling of [12] for formulating our proposal. In this paper we focus on prediction of entries of three-way contingency tables of registered voters with dimensions surname, geolocation, and race/ethnicity. We denote by x_{sgr} the known, correct entries of the three-way table of registered voters in a given state. The index sgr corresponds to the sth surname, g^{th} geolocation, and r^{th} race/ethnicity for $s = 1, \ldots, n_s$, $g = 1, \ldots, n_g$, and $r = 1, \ldots, n_r$, where n_s denotes the number of surnames in the census list, n_g the number of geographic regions (e.g., county), and n_r the number of races/ethnicities (usually six). We denote by m_{sgr} predictions of x_{sgr}. In accordance with [12] we denote summing over components of x_{sgr} with a + subscript. So $x_{+gr} = \sum_s x_{sgr}$ is the two-way table of race by geolocation and $x_{+g+} = \sum_s \sum_r x_{sgr}$ is the vector of geolocations.

In the usual formulation of BISG, predictions are normalized such that for any (s, g) pair the sum of predictions over race is one. A trivial modification of the BISG formula instead results in estimates of the number of people in each cell x_{sgr}. For convenience and readability, we use this formula of BISG, which can be expressed as

$$m_{sgr} = \frac{x^*_{+gr} x^*_{s+r}}{x^*_{++r}}, \tag{1}$$

where x^*_{sgr} denotes the joint distribution of surname, geolocation, and race/ethnicity of the U.S. population. The full joint distribution x^*_{sgr} of the U.S. population is not publicly available, but the margins that appear in equation (1) are provided by the Census. We propose estimating x_{sgr} with a prediction of the form

$$m_{sgr} = x^*_{+gr}\, x^*_{s+r}\, x_{sg+} \exp(\theta_r + \theta_{sg}) \tag{2}$$

where x_{sg+} denotes the joint distribution of surname and geolocation of registered voters. The terms θ_r, θ_{sg} are fit via raking such that our predictions' race/ethnicity margin m_{++r} and surname by geolocation margin m_{+sg} match known totals. A key difference between the parametric form of our proposal, (2), and BISG, (1), is the term x_{sg+}, the joint distribution of surname and geolocation. The presence of this term means that our raking estimates, unlike BISG, do not assume that geolocation and surname are independent conditional on race. The term x_{sg+} also allows us to evaluate, and correct via raking, the prediction's marginal distribution of race/ethnicity in a state.

Raking predictions for registered voters can be computed by first evaluating BISG predictions for the all registered voters in the state, and then raking those predictions to the known margins x_{++r} and x_{sg+}. The resulting estimates, m_{sgr} in (2), have the property that their margins coincide with the known margins. That is,

$$m_{++r} = x_{++r} \quad \text{and} \quad m_{sg+} = x_{sg+}. \tag{3}$$

For registered voters, the margin x_{sg+} can be obtained from publicly available voter registration lists and the racial breakdown of the registered voters in a state can be obtained from the Voter Supplement of the Current Population Survey.

The parametric form of our predictions, (2), was chosen based on availability of accurate margins x_{++r}, x_{sg+}. Unfortunately for the accuracy of our predictions, the race by geolocation margin x_{+gr} is generally unavailable for registered voters. If it were available, we would also rake to that margin

and (2) would include the factor $\exp(\theta_{rg})$. In other applications, however, another set of margins may be known, and thus a parametric form other than (2) could be used.

The predictions obtained through raking, such as in (2), have theoretical properties that have been well-studied [12]. For example, (2) are the unique predictions of the specified parametric form that coincide with the known margins. They also minimize the KL-divergence to the BISG estimates among all predictions that coincide with the known margins [18].

3. Results

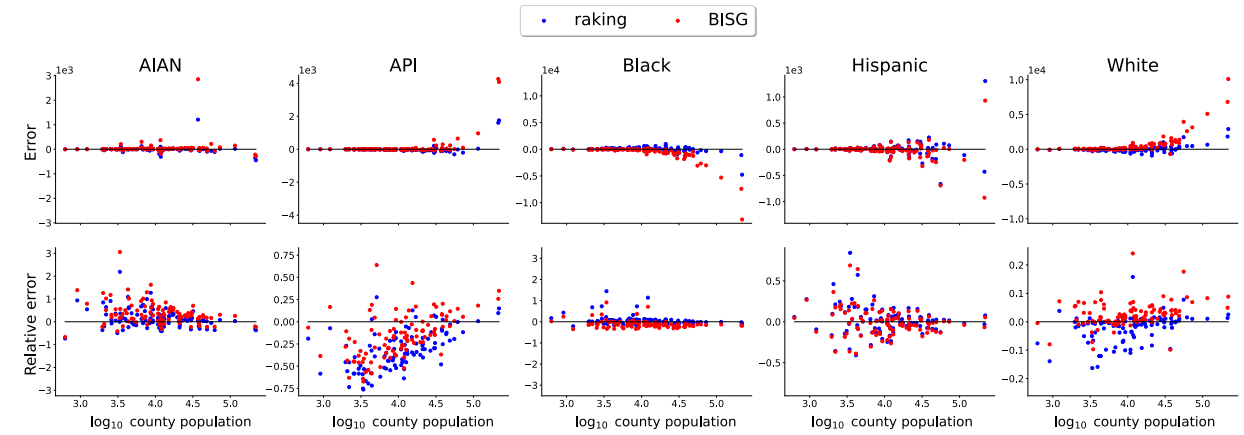
We validate the proposed method on predicting race/ethnicity of registered voters in Florida and North Carolina. Both of these states provide a publicly available data set that includes name, address, and self-identified race/ethnicity of registered voters. The registered voter lists include relevant information on voters that we do not use in this paper. That information is used in prediction methods such as [35, 30] and can be combined with the methods of this paper.

We make predictions using BISG and raking for the three-way contingency table x_{sgr} for registered voters in Florida and North Carolina with dimensions surname, geolocation, and race. For geolocation, we use a county-level discretization.[5] For race/ethnicity, we use categories American Indian and Alaskan native (AIAN), Asian and Pacific Islander (API), non-Hispanic Black, Hispanic, non-Hispanic White, and other.

Predictions using both BISG and our proposal assume a distribution on race/ethnicity of registered voters that is estimated in the Voter Supplement of the Current Population Survey (CPS), which is collected in November of congressional election years. The race/ethnicity distribution estimated by survey data differs from the labeled race/ethnicity of state-provided voter file lists. In some cases, such as Florida in 2020, the differences are minor, whereas in others, such as North Carolina in 2010 and 2020, differences are larger. Differences between the CPS survey data and voter file lists are due to several factors: sampling error, nonresponse in both survey and voter lists, designations of race/ethnicity (see Appendix D), and slightly different timeframes for collection of data. For performing validation on voter registration lists in North Carolina and Florida, we use two strategies for calibrating the test set (registered voters) with the population on which the predictions were trained (CPS). In one approach, we subsample voter file lists so that the race/ethnicity distribution of the test set (registered voters) coincides with the CPS estimate of the race/ethnicity distribution of registered voters. In the other approach, we make predictions on the full set of registered voters in the state (using the CPS-assumed distribution of race/ethnicity) and then map those predictions onto the race/ethnicity distribution of the voter file using a calibration map. Results of validation using the calibration map are presented in Appendix E and the construction of the calibration map is described in Appendix C.

We compare the accuracy of our prediction algorithm, described in Section 2, to BISG. While BISG is often implemented by obtaining its factors (probability of geolocation given race and probability of race given surname) from census data from the full population, we adjust the usual BISG factors to correspond to the population of registered voters in Florida and North Carolina using the strategy of [35]. We provide details on our BISG implementation in Appendix B. We evaluate performance using two categories of metrics, subpopulation estimation (or mean errors) and individual-level errors. To evaluate subpopulation estimates in a county, we first compute race/ethnicity predictions for each registered voter in that county, and then sum the estimates

[5] Recent work has shown that the accuracy of BISG can benefit from finer discretizations than county [15]. The raking approach of this paper can be used with any geographic discretization, though we leave validation of discretizations other than county to future work.



	AIAN	API	Black	Hispanic	White
% of state:	1.9%	3.1%	22.7%	5.2%	66.2%
Rake % of state:	1.9%	3.1%	22.7%	5.2%	66.2%
BISG % of state:	2.1%	3.6%	19.7%	5.1%	69.0%
Rake Mean Error:	0%	0%	0%	0%	0%
BISG Mean Error:	12%	17%	-13%	-2%	4%
Rake Mean Abs. Error:	12%	12%	5%	6%	2%
BISG Mean Abs. Error:	18%	21%	14%	7%	5%

Figure 2: *Errors in subpopulation estimation for subsampled registered voters in each county in North Carolina in 2020 for two methods, BISG and raking. Each dot in the scatterplots represents error in one county. Dots above the horizontal line correspond to overestimating the size of a subpopulation size in one county. Dots below the horizontal line indicate underestimating.*

(vectors in $\mathbb{R}^6$) over each person. This procedure, sometimes known as weighting or a weighted estimator [14], results in an estimate, under a prediction scheme, of the race/ethnicity distribution of the registered voters in the county. We then compare that distribution to the true distribution of the county, obtained from the labeled data set. We report these errors in Figures 1, 2, and 9. Details on the error metrics are provided in Appendix E.

Individual-level errors compare a prediction for particular surname, geolocation pairs (e.g., Martinez, Miami-Dade County) to the empirical, true distribution. We compare the prediction and ground truth (vectors in $\mathbb{R}^6$) in ℓ^1, ℓ^2, and we evaluate the negative log-likelihood under a multinomial model. We report these error metrics aggregated at the region level in Table 2.

While predictions in Florida and North Carolina are for validation purposes (we have the self-identified race of registered voters), in other states, we have the surname-by-geolocation and race/ethnicity margins, but no race/ethnicity labels for each registered voter. We implement our algorithm and BISG (in addition to several other predictions) in several such states: New York, Ohio, Oklahoma, Vermont, and Washington.[6]

4. Discussion and conclusion

In this paper, we have shown that statistical dependence of surname and location by race/ethnicity results in systematic inaccuracies in BISG. We have proposed a novel algorithm for predicting the joint distribution of race/ethnicity, geolocation, and surname. Our algorithm relaxes BISG's independence assumption, is mathematically straightforward, easily interpretable, and noticeably more accurate than BISG. Instead of viewing BISG as a race/ethnicity imputation algorithm for individual surname and geolocation pairs, we view it as estimating entries of a contingency table

[6] An implementation and predictions are available at `https://github.com/pgree/raking_bisg/`

with dimensions race/ethnicity, geolocation, and surname. We use raking, a classical tool in the analysis of tabular data [12], to combine the inputs to BISG with publicly available margins.

By using the joint distribution of surname and geolocation from state voter files in combination with survey data, our method produces an accurate estimate of the statewide distribution of race/ethnicity. This is a property that BISG does not have at any geographic region. With BISG, statewide mean errors are generally large and errors are often correlated with total county population (and subpopulation size), which can introduce bias in racial disparity estimation [14]. We validate our method on predicting race/ethnicity of registered voters in Florida and North Carolina. Unlike BISG, the proposed method benefits from being unbiased in the sense that for any race/ethnicity, the mean error across all registered voters in a state is zero. Our method is also better calibrated than BISG. The Kuiper metrics for measuring calibration (Table 7) demonstrate clear improvement [47].[7] On the other hand, like with BISG, the errors of our method are usually correlated with county population size.

In this paper we validate and fit our method on the same population—registered voters. However, our algorithm, like BISG, can be applied to test sets that differ from the data set it was fit on. BISG is used in a wide range of applications, including for enrollees in health plans [25], users of social media [4], and registered voters [1]. In all of these cases, BISG is applied to populations different from the one it was fit on—the full U.S. population. It is possible to account for differences between the train and test populations using adjustments like the logistic regression approach of [25] or the approach of [35], which we use in this paper (see Appendix B for details). Similar approaches could be used to adjust this paper's raking-based estimates trained on the registered voter population. Comparing our method and BISG on application domains other than registered voters is an area of future study.

There are many natural generalizations of this work. The methods of [30] include BISG generalizations for healthcare applications that use logistic regression for incorporating additional features. Similar strategies could be fruitful for improving accuracy of our method. These methods would likely involve training on labeled data in certain geographic regions to generalize to unlabeled data in other areas. Other potential generalizations include raking on the logistic scale, and the use of additional features for training, such as sex, first name, etc.

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A. The BISG independence assumption

In this section we illustrate the impacts of BISG's conditional independence assumption using data sets of registered voters in Florida in December 2020 and North Carolina in November 2010 and November 2020. In Florida and North Carolina, publicly available state voter files include name, address, and self-identified race/ethnicity.[8] By using these data sets to fit BISG predictions and test their accuracy, we isolate the impact of BISG's conditional independence assumption.

We first describe BISG's conditional independence assumption. Given an individual's surname, s, and geolocation, g, the BISG prediction of race/ethnicity is

$$\mathbb{P}(r|g,s) = \frac{\mathbb{P}(g|r)\,\mathbb{P}(r|s)}{\sum_i \mathbb{P}(g|r_i)\,\mathbb{P}(r_i|s)} = \frac{\mathbb{P}(r|g)\,\mathbb{P}(r|s)\;\mathbb{P}(r)}{\sum_i \mathbb{P}(r_i|g)\,\mathbb{P}(r_i|s)/P(r_i)} \tag{4}$$

where $r_1, \ldots, r_m$ correspond to m racial groups (usually $m = 6$ in practice) and s, g signify surname and geolocation. This formula is exact under the assumption that surname and geolocation are conditionally independent on race/ethnicity, that is, $s|r$ and $g|r$ are independent.

To isolate the effects of BISG's independence assumption, we use labeled state voter files to both construct the factors $\mathbb{P}(r), \mathbb{P}(r|g), \mathbb{P}(r|s)$ in BISG and to test the resulting BISG predictions. Specifically, each factor is evaluated in the following way.

- $\mathbb{P}(r|g)$ is computed for each race/ethnicity r by taking the total number of registered voters of race r in geographic region g and dividing that number by the total number of people in g.
- $\mathbb{P}(r)$ is, for each race/ethnicity r, the fraction of registered voters in the full state who identify as race/ethnicity r.
- $\mathbb{P}(r|s)$ is computed by dividing the total number of registered voters with surname s and race/ethnicity r by the total number of people with surname s.

We then compute the BISG estimate for each registered voter. We do this same procedure separately for Florida in 2020, North Carolina in 2020 and North Carolina in 2010.[9]

We use several metrics to report the accuracy of BISG fit and tested on Florida and North Carolina voter files. Recall that since each factor used in the evaluation of BISG is exact, all deviation from perfect accuracy is due to BISG's conditional independence assumption. Figures 3-5 show the absolute and relative errors of BISG subpopulation estimates in each county and region; see (13), (14) for formal definitions of these metrics. In Table 1, we report errors of the subpopulation estimates of BISG on the full state and in Table 2 we provide region-level ℓ^1, ℓ^2 errors and negative log-likelihood (see (17), (18), (19)). Codes for generating these tables and figures as well as tables of county-level errors are publicly available[10]. All metrics used for evaluating accuracy are defined in Appendix E.

[8] In North Carolina there is a high rate of nonresponse on self-identified race/ethnicity, whereas in Florida, nonresponse is relatively rare.

[9] We remove from this analysis those with "inactive" registrations and those who did not answer the race/ethnicity question.

[10] https://github.com/pgree/raking_bisg

While statewide subpopulation estimates using BISG can be accurate, Figures 3, 4, 5 demonstrate that subpopulation estimation over smaller geographic regions is often highly inaccurate, with smaller regions and smaller subpopulations suffering from large relative errors. In 88% of counties in Florida, Hispanic populations were underestimated, and in 90% of counties API were undercounted. For many subpopulations, BISG errors are strongly correlated with the size of the county population. County population size (and also BISG errors) are correlated with various features including subpopulation size, subpopulation percentage of county population, and rurality. In this paper we do not investigate which of these features may cause the observed BISG errors.

One strength of BISG is that when estimating subpopulations over the full state (or a reasonably large uniform sample), the errors are often small. Unfortunately, in practice this is not a very useful feature. Data sets are rarely uniformly sampled over the full population and if they are, predictions can be made using the features of the full population.

	AIAN	API	Black	Hispanic	White	Other
True	41,132	246,037	1,762,643	1,933,318	7,799,621	279,677
BISG	41,160	244,489	1,725,555	1,969,591	7,805,264	276,366
Error	28	-1,547	-37,087	36,273	5,643	-3,310
Relative Error	0.07%	-0.63%	-2.10%	1.88%	0.07%	-1.18%

(a) *Florida 2020*

	AIAN	API	Black	Hispanic	White	Other
True	37,843	51,584	933,877	104,935	3,277,490	73,432
BISG	43,717	54,204	939,154	106,517	3,262,175	73,392
Error	5,874	2,620	5,277	1,582	-15,314	-39
Relative Error	15.52%	5.08%	0.57%	1.51%	-0.47%	-0.05%

(b) *North Carolina 2020*

	AIAN	API	Black	Hispanic	White	Other
True	37,337	20,258	890,308	48,027	3,434,953	53,215
BISG	43,013	21,679	900,756	49,711	3,415,321	53,615
Error	5,676	1,421	10,448	1,684	-19,631	400
Relative Error	15.20%	7.02%	1.17%	3.51%	-0.57%	0.75%

(c) *North Carolina 2010*

Table 1: *Errors in statewide subpopulation estimation for BISG separately fit and tested on each state voter file.*

B. BISG for registered voters

The BISG formula (4) is usually calculated using census data on the full population. The probability of a person belonging to a geographic region given race, $\mathbb{P}(g|r)$ and the probability of race/ethnicity given surname, $\mathbb{P}(r|s)$, are both obtained from the decennial census for the full U.S. population.

Unfortunately, the decennial census does not provide those same distributions for registered voter populations in any state or the full United States. However, the Census Bureau does conduct the Current Population Survey (CPS) which contains a biannual Voter Supplement that includes questions about voter registration status. This information can be combined with the decennial census to obtain BISG estimates on the registered-voter population. We combine information from

	ℓ^1 errors			ℓ^2 errors			negative log-likelihood		
Region	BISG	$r\|g$	$r\|s$	BISG	$r\|g$	$r\|s$	BISG	$r\|g$	$r\|s$
Central	0.174	0.813	0.213	0.107	0.489	0.134	0.213	0.455	0.219
Centraleast	0.166	0.549	0.226	0.104	0.332	0.142	0.193	0.349	0.201
Centralwest	0.152	0.572	0.219	0.095	0.344	0.139	0.194	0.362	0.204
Northcentral	0.263	0.614	0.341	0.169	0.377	0.218	0.242	0.382	0.257
Northeast	0.188	0.566	0.298	0.118	0.341	0.191	0.236	0.383	0.254
Northwest	0.214	0.405	0.318	0.135	0.246	0.202	0.211	0.292	0.229
Southeast	0.176	0.873	0.272	0.111	0.526	0.175	0.224	0.478	0.245
Southwest	0.144	0.529	0.244	0.091	0.329	0.156	0.143	0.302	0.160
Florida	0.175	0.686	0.253	0.110	0.414	0.161	0.209	0.405	0.223

(a) *Florida 2020*

	ℓ^1 errors			ℓ^2 errors			negative log-likelihood		
Region	BISG	$r\|g$	$r\|s$	BISG	$r\|g$	$r\|s$	BISG	$r\|g$	$r\|s$
Central	0.199	0.541	0.264	0.130	0.336	0.174	0.206	0.347	0.217
East	0.301	0.578	0.379	0.199	0.368	0.251	0.237	0.346	0.261
West	0.116	0.199	0.339	0.076	0.124	0.226	0.092	0.139	0.142
North Carolina	0.216	0.510	0.303	0.142	0.320	0.200	0.201	0.322	0.220

(b) *North Carolina 2020*

	ℓ^1 errors			ℓ^2 errors			negative log-likelihood		
Region	BISG	$r\|g$	$r\|s$	BISG	$r\|g$	$r\|s$	BISG	$r\|g$	$r\|s$
Central	0.189	0.441	0.246	0.127	0.286	0.165	0.183	0.281	0.194
East	0.302	0.544	0.368	0.203	0.357	0.248	0.227	0.316	0.250
West	0.102	0.158	0.306	0.068	0.101	0.207	0.078	0.109	0.124
North Carolina	0.209	0.432	0.288	0.140	0.281	0.193	0.182	0.268	0.200

(c) *North Carolina 2010*

Table 2: *Voter file-only fitting and testing: Accuracy of BISG, geolocation-only ($r|g$), and surname-only ($r|s$) predictions of race/ethnicity of registered voters in Florida in 2020, North Carolina in 2020, and North Carolina in 2010. We report l^1 and l^2 errors and negative log-likelihood for each region.*

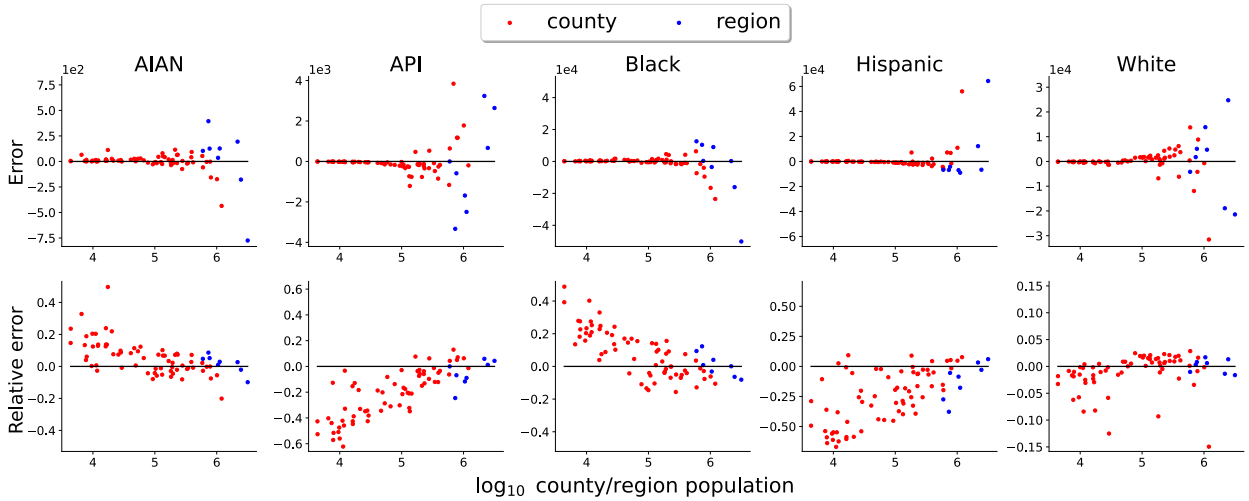


Figure 3: *Errors in subpopulation estimation with BISG predictions in each county and region in Florida in 2020. BISG was fit and tested on the Florida voter file.*

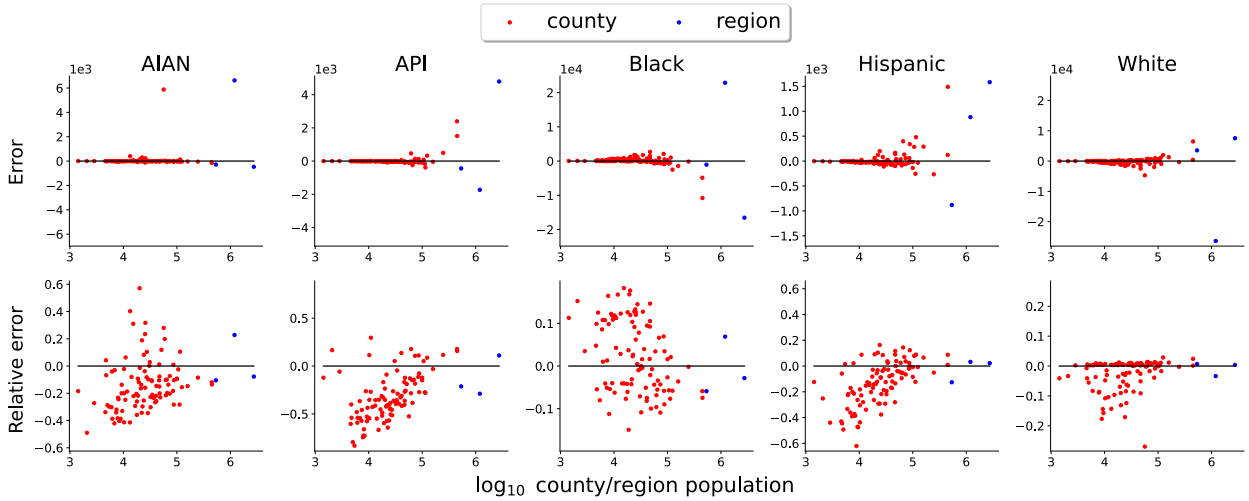


Figure 4: *Errors in subpopulation estimation with BISG predictions in each county in North Carolina in 2020. BISG was fit and tested on the North Carolina voter file.*

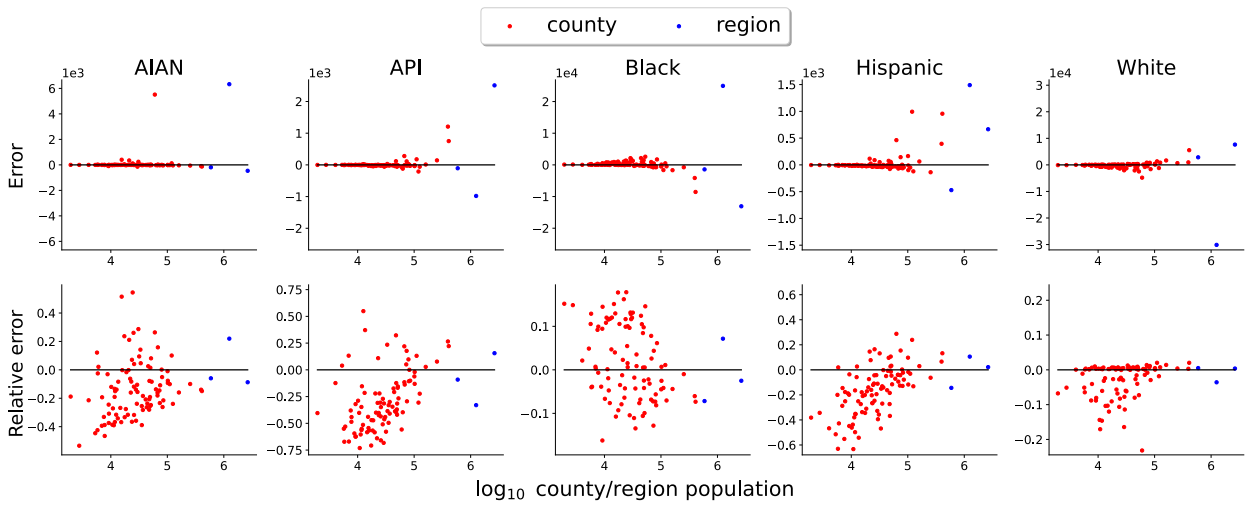


Figure 5: *Errors in subpopulation estimation with BISG predictions in each county in North Carolina in 2010. BISG was fit and tested on the North Carolina voter file.*

the CPS and the decennial census using an approach similar to that of [35].

The method of [35] extends BISG to incorporate demographic information beyond surname and geolocation (in particular age, gender, and party registration). Their method relies on two conditional independence assumptions that we also use here for constructing a BISG for registered voters in a particular state. The assumptions are as follows:

1. For any given race/ethnicity, vote registration status and geographic region are independent. This conditional independence assumption implies

$$\mathbb{P}(v|r,g) = \mathbb{P}(v|r) \tag{5}$$

   where v denotes vote registration status.

2. For any given race/ethnicity, vote registration status and surname are independent, implying

$$\mathbb{P}(v|r,s) = \mathbb{P}(v|r). \tag{6}$$

Combining these two assumptions, we obtain a BISG formula for registered voters. Specifically, we start by modifying the usual BISG formula $\mathbb{P}(r|g,s) \propto \mathbb{P}(r|g)\,\mathbb{P}(r|s)\,/\,\mathbb{P}(r)$ to condition on vote registration status:

$$\mathbb{P}(r|g,s,v) \propto \mathbb{P}(r|g,v)\,\mathbb{P}(r|s,v)\,/\,\mathbb{P}(r|v). \tag{7}$$

Bayes rule tells us

$$\mathbb{P}(r|g,v) \propto \mathbb{P}(v|r,g)\;\mathbb{P}(r|g) \qquad \text{and} \qquad \mathbb{P}(r|s,v) \propto \mathbb{P}(v|r,s)\;\mathbb{P}(r|s). \tag{8}$$

Applying the conditional independence assumptions (5) and (6), we obtain

$$\mathbb{P}(r|g,v) \propto \mathbb{P}(v|r)\;\mathbb{P}(r|g) \qquad \text{and} \qquad \mathbb{P}(r|s,v) \propto \mathbb{P}(v|r)\;\mathbb{P}(r|s). \tag{9}$$

Substituting (9) into (7), we get a BISG for registered voters:

$$\mathbb{P}(r|s,g,v) \propto \mathbb{P}(v|r)\,\mathbb{P}(r|g)\,\mathbb{P}(r|s)\,/\,\mathbb{P}(r). \tag{10}$$

This prediction is equivalent to the usual BISG for the full population multiplied by $\mathbb{P}(v|r)$ and appropriately normalized. The factor $\mathbb{P}(v|r)$ is computed using the CPS estimate for $P(r|v)$ and the census total for $P(r)$ for the above-18 population. This formula is equivalent to formula (7) in [35] where we omit the age and gender features X_i and party registration P_i is replaced with voter registration status.

C. Validation via a calibration map

In Section 2 we describe a raking-based method for predicting race/ethnicity of registered voters. Our method fits predictions to survey data from the CPS on the race/ethnicity distribution of registered voters, and we also fit predictions to the joint distribution of surname and geolocation of registered voters obtained from state voter registration files. For validation, we test those predictions on registered voters in the voter files of Florida and North Carolina which contain self-identified race/ethnicity.

The accuracy of the CPS's registered voter distributions and their consistency with state voter files have been extensively studied in political science communities [5, 42, 26]. In [42] McDonald conjectures that there are two primary sources of error in the CPS's and state voter files' estimates of the race/ethnicity distribution of registered voters. In voter files the primary source of error is likely "deadwood," "persons who are registered at but no longer live at an address." In the CPS, there are two main sources of error: (i) overreport bias [31, 34], the phenomenon by which people claim to have voted, or be registered to vote even when they are not, and (ii) the CPS, partially to counteract this effect, count all "don't know" or nonresponse as not being registered to vote.

In this paper we do not attempt to adjust for these factors directly. Instead, we calibrate the CPS and voter file using two approaches. First, as described in Section 3, we subsample voter files such that the race/ethnicity distribution of the subsample coincides with the CPS estimate of the race/ethnicity distribution of registered voters in the state. That is, we ensure that the race/ethnicity distribution used for fitting predictions is the same as the distribution of the test set. In the second approach, described in this section, we construct a calibration map from predictions trained on the CPS-assumed population of registered voters to make predictions on the state voter file set of registered voters.[11]

For our calibration map, we use a 6×6 matrix (where we have 6 races/ethnicities) and impose two properties: (i) the matrix is "stochastic," that is, it transforms a probability distribution (a vector whose entries are non-negative and sum to one) to another probability distribution, and (ii) the matrix maps the CPS distribution to the voter file distribution. Such a matrix exists for any CPS and voter file distributions. For example, if $u_{\text{cps}} \in \mathbb{R}^6$ is the probability distribution of the CPS and $u_{\text{vf}} \in \mathbb{R}^6$ is the probability distribution of the voter file, then the linear map $u_{\text{vf}}\mathbb{1}$ satisfies the above conditions where $\mathbb{1}$ denotes the row vector in $\mathbb{R}^6$ with all ones, that is, $\mathbb{1} = [1, ..., 1]$.

In general, a map such as $u_{\text{vf}}\mathbb{1}$ has features that are undesirable for the purposes of a calibration map. Consider the simple example where the CPS and voter file probability distributions are identical, or $u_{\text{cps}} = u_{\text{vf}}$. Then $u_{vf}\mathbb{1}$ satisfies

$$u_{\text{vf}}\mathbb{1} = \begin{bmatrix} — & u_{\text{vf}} & — \\ — & u_{\text{vf}} & — \\ & \vdots & \\ — & u_{\text{vf}} & — \end{bmatrix}, \tag{11}$$

[11] The CPS uses a different classification of race/ethnicity than Florida (see Appendix D). We use the method described in [42] for converting the CPS classification to those of state voter files.

though if the CPS and voter file distributions are identical a more natural map would be the identity matrix. In general, the calibration map should minimize, to the extent possible, "redistributing" subpopulations.[12]

To find such a matrix, we solve the following constrained convex optimization problem. We seek the 6×6 stochastic matrix A that minimizes the Frobenius norm of the difference between A and the identity matrix such that $Au_{\text{cps}} = u_{\text{vf}}$. That is, we seek

$$\arg\min_{A}\{\|A - I\|_F : A_{i,j} \geq 0 \text{ for all } i, j \in \{1, ..., 6\},\ \mathbb{1}A = \mathbb{1},\ \text{and } Au_{\text{cps}} = u_{\text{vf}}\}. \tag{12}$$

We solve this optimization with the Python package cvxpy [23], [3].

D. Race/ethnicity classification

The data sets we use in this paper—the CPS, the decennial census redistricting files, the surname list of the decennial census, and the Florida and North Carolina voter files—all have different categorizations of race. For each of these sources, we map the race/ethnicity categories provided into six groups: American Indian and Alaskan native (AIAN), Asian and Pacific Islander (API), non-Hispanic Black, Hispanic, non-Hispanic White, and other. We provide here our mapping:

- Decennial census surname list: Contains six categories—"Non-Hispanic White Alone, Non-Hispanic Black or African American Alone, Non-Hispanic American Indian and Alaska Native Alone, Non-Hispanic Asian and Native Hawaiian and Other Pacific Islander Alone, Non-Hispanic Two or More Races, and Hispanic or Latino origin." These were mapped onto our categories in the natural way with "two or more race" being mapped onto our category "other."

- Decennial census redistricting files: Respondents are asked for Hispanic/non-Hispanic origin and in a separate question respondents are asked which race they identify as among AIAN, API, Black, White, Other, and two or more races. To map onto our categorization, all those of Hispanic origin were included in Hispanic. Those who identified as two or more races in the census were placed in the "other" group.

- Current population survey: Like in the decennial census, all respondents are asked Hispanic/non-Hispanic origin and separately respondents are asked detailed race questions. For this mapping, we use the classification of [42] : "All CPS respondents reporting Hispanic ethnicity are scored as Hispanic. All non-Hispanics reporting a single race only are reported as that race. Asian and Hawaiian-Pacific Islander are grouped into an Asian category. For multiple-race categories, non-Hispanics reporting Black in any other combination are scored as Black. Among the remainder, non-Hispanics reporting Asian or Hawaiian-Pacific Islander in combination with any other remaining race are identified as Asian. Those remaining are classified as other."

- Florida voter file: Includes race/ethnicity groups: "American Indian/ Alaskan Native" (AIAN), "Asian/Pacific Islander (API)," "Black, *not of* Hispanic Origin," "Hispanic," "White, *not of* Hispanic Origin," "Multi-racial," "Other." We included all "multi-racial" in our "other" bucket.

[12] This is closely related to a set of problems that have been formalized in the optimal transport literature. See for example, Section 2.3 of [43].

- North Carolina voter file: Includes separate fields for Hispanic origin and race. All Hispanics are included in the "Hispanic" group. Among the remaining, classifications were made in the natural way and "multi-racial" were included in "other."

E. Detailed results

We use several error metrics for validation in this paper. Here, we provide formulas for these metrics. As in Section 2, we denote by x_{sgr} the correct values of the surname by geolocation by race/ethnicity contingency table and we denote by m_{sgr} the corresponding predictions. We denote by a subscript "+" summing over an index. So, x_{+gr} and m_{+gr} denote summing over the surname index for the correct and predicted values respectively.

Subpopulation estimation

- Absolute error:

$$x_{+gr} - m_{+gr} \tag{13}$$

for $g = 1, \ldots, n_g$ and $r = 1, \ldots, 6$.

- Relative error:

$$\frac{x_{+gr} - m_{+gr}}{x_{+gr}} \tag{14}$$

for $g = 1, \ldots, n_g$ and $r = 1, \ldots, 6$.

- Mean absolute deviation:

$$\sum_{g=1}^{n_g} |x_{+gr} - m_{+gr}| \tag{15}$$

for $r = 1, \ldots, 6$.

- Average errors:

$$x_{++r} - m_{++r} \tag{16}$$

for $r = 1, \ldots, 6$.

ℓ^1, ℓ^2 and negative log-likelihood

- ℓ^1 error:

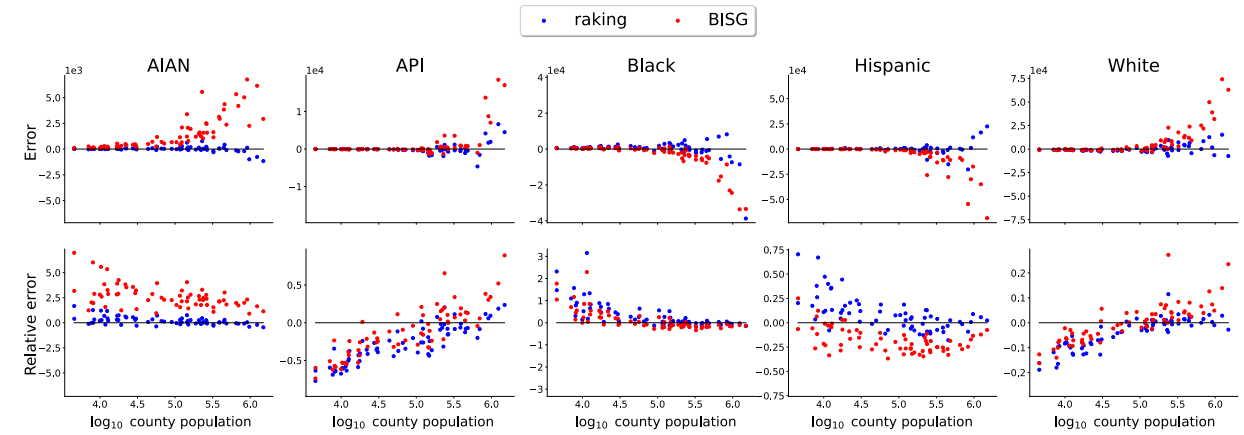
$$\frac{1}{x_{+g+}} \sum_{s=1}^{n_s} \sum_{r=1}^{6} |x_{sgr} - m_{sgr}| \tag{17}$$

for $g = 1, \ldots, n_g$.

- ℓ^2 error:

$$\frac{1}{x_{+g+}} \sum_{s=1}^{n_s} \left(\sum_{r=1}^{6} (x_{sgr} - m_{sgr})^2 \right)^{1/2} \tag{18}$$

for $g = 1, \ldots, n_g$.



	AIAN	API	Black	Hispanic	White
% of state:	0.3%	2.1%	13.9%	18.0%	63.1%
Rake % of state:	0.3%	2.1%	13.9%	18.0%	63.1%
BISG % of state:	1.0%	2.7%	12.3%	15.2%	66.4%
Rake Mean Error:	0%	0%	0%	0%	0%
BISG Mean Error:	209%	25%	-11%	-16%	5%
Rake Mean Abs. Error:	20%	14%	8%	5%	2%
BISG Mean Abs. Error:	209%	30%	13%	16%	6%

Figure 6: *Errors in subpopulation estimation for registered voters in each county in Florida in 2020 for two methods, BISG and raking, using a calibration map. Each dot in the scatterplots represents error in one county with BISG or raking. Dots above the horizontal line correspond to overestimating the size of a subpopulation size in one county. Dots below the horizontal line indicate underestimating.*

- Negative log-likelihood:

$$-\frac{1}{x_{+g+}} \sum_{s=1}^{n_s} \sum_{r=1}^{6} x_{sgr} \log(m_{sgr}) \tag{19}$$

All raking and BISG predictions of this section are computed using the methods described in Section 3 and details of the BISG implementation are provided in Appendix B. Raking predictions are computed by raking to CPS race/ethnicity margins and surname by geolocation margins of state voter files.

We illustrate the accuracy of raking and BISG for both approaches to validation, subsampling and the calibration map (see Appendix C) in the following figures and tables. We include subpopulation estimation accuracy in Florida in 2020 with subsampling in Figure 1 and calibration map in Figure 6. Those same metrics are reported in North Carolina in 2020 (Figures 2 and 8), and in North Carolina in 2010 (Figures 9 and 10). In each of the above figures, the scatterplots provide absolute and relative errors (13) and (14) and each dot corresponds to one subpopulation in one county. The bar plots of the above figures report mean absolute deviation (15) and average error (16).

We also include ℓ^1, ℓ^2 errors and negative log-likelihood (see (17), (18), and (19)) by region in Florida in 2020 (Table 3), North Carolina in 2020 (Table 4), and North Carolina in 2010 (Table 5).

Table 6 provides various relevant race/ethnicity distributions including those of state voter files, the CPS, and the decennial census.

In addition to reporting the above accuracy metrics, we measure calibration of raking and BISG predictions using the methods and software implementation of [47]. Specifically, we graphically

	ℓ^1 errors		ℓ^2 errors		negative log-likelihood	
Region	raking	BISG	raking	BISG	raking	BISG
Central	0.362	0.365	0.227	0.227	0.271	0.285
Centraleast	0.260	0.261	0.165	0.165	0.219	0.226
Centralwest	0.266	0.270	0.168	0.169	0.228	0.235
Northcentral	0.352	0.358	0.230	0.232	0.255	0.260
Northeast	0.286	0.293	0.181	0.184	0.260	0.265
Northwest	0.269	0.274	0.172	0.172	0.220	0.224
Southeast	0.393	0.402	0.245	0.249	0.281	0.286
Southwest	0.257	0.234	0.165	0.149	0.179	0.181
Florida	0.323	0.327	0.204	0.205	0.250	0.257

(a) *Florida 2020, subsampling*

	ℓ^1 errors		ℓ^2 errors		negative log-likelihood	
Region	raking	BISG	raking	BISG	raking	BISG
Central	0.381	0.387	0.231	0.234	0.305	0.319
Centraleast	0.281	0.283	0.173	0.173	0.250	0.256
Centralwest	0.286	0.289	0.174	0.175	0.257	0.264
Northcentral	0.383	0.384	0.242	0.240	0.293	0.297
Northeast	0.305	0.311	0.187	0.190	0.291	0.295
Northwest	0.295	0.293	0.183	0.178	0.246	0.249
Southeast	0.404	0.415	0.243	0.249	0.317	0.323
Southwest	0.275	0.257	0.170	0.158	0.202	0.205
Florida	0.341	0.345	0.208	0.210	0.282	0.289

(b) *Florida 2020, calibration map*

Table 3: *Florida 2020 validation via subsampling and calibration map:* ℓ^1, ℓ^2 *errors and negative log-likelihood in each region.*

	ℓ^1 errors		ℓ^2 errors		negative log-likelihood	
Region	raking	BISG	raking	BISG	raking	BISG
Central	0.379	0.381	0.239	0.242	0.287	0.291
East	0.461	0.458	0.297	0.296	0.308	0.309
West	0.218	0.205	0.139	0.132	0.141	0.140
North Carolina	0.383	0.382	0.244	0.244	0.276	0.279

(a) *North Carolina 2020, subsampling*

	ℓ^1 errors		ℓ^2 errors		negative log-likelihood	
Region	raking	BISG	raking	BISG	raking	BISG
Central	0.350	0.340	0.218	0.217	0.265	0.268
East	0.436	0.424	0.278	0.275	0.287	0.290
West	0.189	0.159	0.116	0.100	0.117	0.115
North Carolina	0.354	0.341	0.222	0.218	0.254	0.256

(b) *North Carolina 2020, calibration map*

Table 4: *North Carolina 2020 validation via subsampling and calibration map:* ℓ^1, ℓ^2 *errors and negative log-likelihood in each region.*

Region	ℓ^1 errors raking	ℓ^1 errors BISG	ℓ^2 errors raking	ℓ^2 errors BISG	negative log-likelihood raking	negative log-likelihood BISG
Central	0.323	0.336	0.211	0.215	0.240	0.243
East	0.445	0.452	0.293	0.293	0.285	0.286
West	0.173	0.178	0.113	0.115	0.113	0.113
North Carolina	0.339	0.349	0.222	0.224	0.236	0.239

(a) *North Carolina 2010, subsampling*

Region	ℓ^1 errors raking	ℓ^1 errors BISG	ℓ^2 errors raking	ℓ^2 errors BISG	negative log-likelihood raking	negative log-likelihood BISG
Central	0.288	0.288	0.187	0.186	0.223	0.224
East	0.412	0.409	0.269	0.267	0.268	0.269
West	0.147	0.139	0.093	0.088	0.095	0.095
North Carolina	0.304	0.302	0.197	0.196	0.219	0.220

(b) *North Carolina 2010, calibration map*

Table 5: *North Carolina 2010 validation via subsampling and calibration map:* ℓ^1, ℓ^2 *errors and negative log-likelihood in each region.*

Population	AIAN	API	Black	Hispanic	White	Other
USA census 2020	0.007	0.061	0.121	0.187	0.578	0.046
FL 2020 census	0.002	0.030	0.145	0.265	0.515	0.043
FL 2020 18+ census	0.002	0.030	0.135	0.250	0.547	0.036
FL 2020 CPS voters	0.004	0.028	0.141	0.190	0.636	0.001
FL 2020 voter file	0.003	0.021	0.139	0.180	0.631	0.025

(a) *Florida 2020*

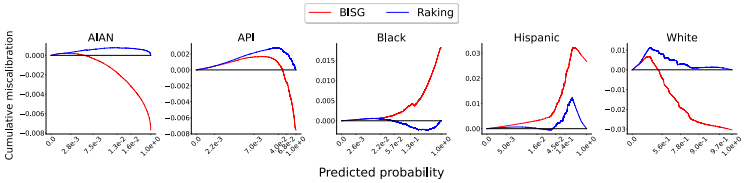
Population	AIAN	API	Black	Hispanic	White	Other
USA census 2020	0.007	0.061	0.121	0.187	0.578	0.046
NC 2020 census	0.010	0.033	0.202	0.107	0.605	0.043
NC 2020 18+ census	0.009	0.032	0.199	0.089	0.636	0.034
NC 2020 CPS voters	0.019	0.031	0.227	0.052	0.662	0.009
NC 2020 voter file	0.008	0.013	0.204	0.029	0.728	0.018

(b) *North Carolina 2020*

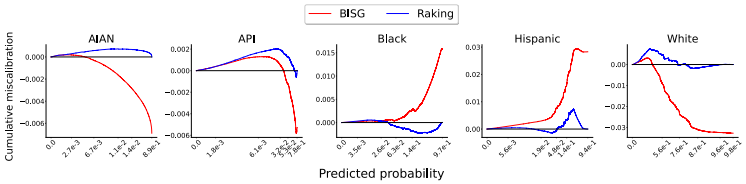
Population	AIAN	API	Black	Hispanic	White	Other
USA census 2010	0.007	0.048	0.122	0.163	0.637	0.021
NC 2010 census	0.011	0.022	0.212	0.084	0.653	0.018
NC 2010 18+ census	0.011	0.022	0.204	0.068	0.684	0.011
NC 2010 CPS voters	0.022	0.018	0.201	0.024	0.730	0.005
NC 2010 voter file	0.008	0.005	0.195	0.012	0.767	0.013

(c) *North Carolina 2010*

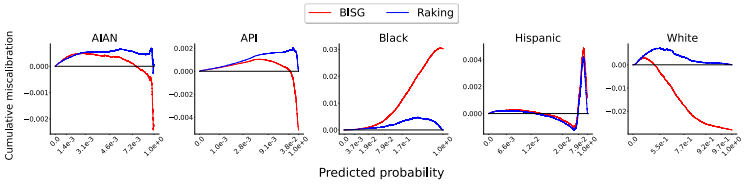
Table 6: *Various race/ethnicity distributions in Florida and North Carolina.*



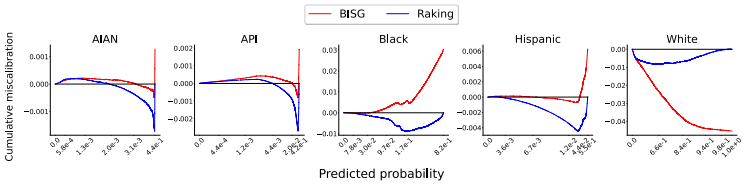
(a) *2020 Florida, subampled*



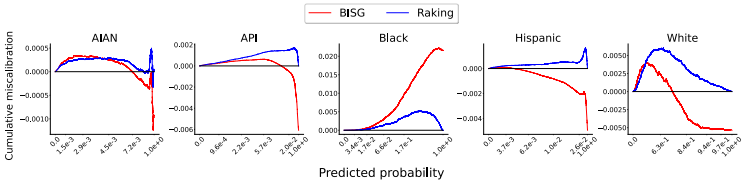
(b) *2020 Florida, calibration map*



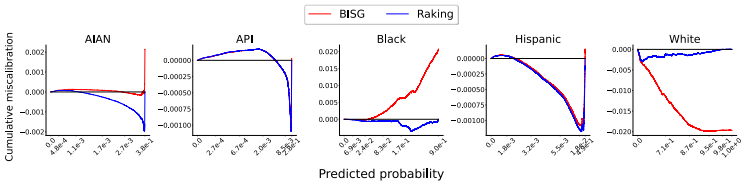
(c) *2020 North Carolina, subampled*



(d) *2020 North Carolina, calibration map*



(e) *2010 North Carolina, subampled*



(f) *2010 North Carolina, calibration map*

Figure 7: *Cumulative miscalibration of BISG and raking on registered voters in Florida and North Carolina. The vertical axis represents cumulative deviation from perfect calibration. The slope of a line connecting any two points on the curve is the average miscalibration for the predicted probabilities between those two points. Flatter curves near zero represent better calibration. The ticks on the horizontal axis are quintiles of BISG predictions. Non-uniform spacing between quintiles is due to weighting more frequently-appearing (surname, geolocation) pairs in estimating miscalibration.*

	AIAN	API	Black	Hispanic	White
FL 2020 BISG	0.0079	0.0092	0.0182	0.0322	0.0371
FL 2020 raking	0.0008	0.0028	0.0029	0.0128	0.0112

(a) *Florida 2020, subsampled*

	AIAN	API	Black	Hispanic	White
FL 2020 BISG	0.0071	0.0071	0.0158	0.0293	0.0358
FL 2020 raking	0.0007	0.0026	0.0028	0.0088	0.0093

(b) *Florida 2020, calibration map*

	AIAN	API	Black	Hispanic	White
NC 2020 BISG	0.0029	0.0061	0.0305	0.0059	0.0311
NC 2020 raking	0.0010	0.0020	0.0047	0.0054	0.0072

(c) *North Carolina 2020, subsampled*

	AIAN	API	Black	Hispanic	White
NC 2020 BISG	0.0018	0.0028	0.0306	0.0070	0.0454
NC 2020 raking	0.0019	0.0029	0.0088	0.0045	0.0085

(d) *North Carolina 2020, calibration map*

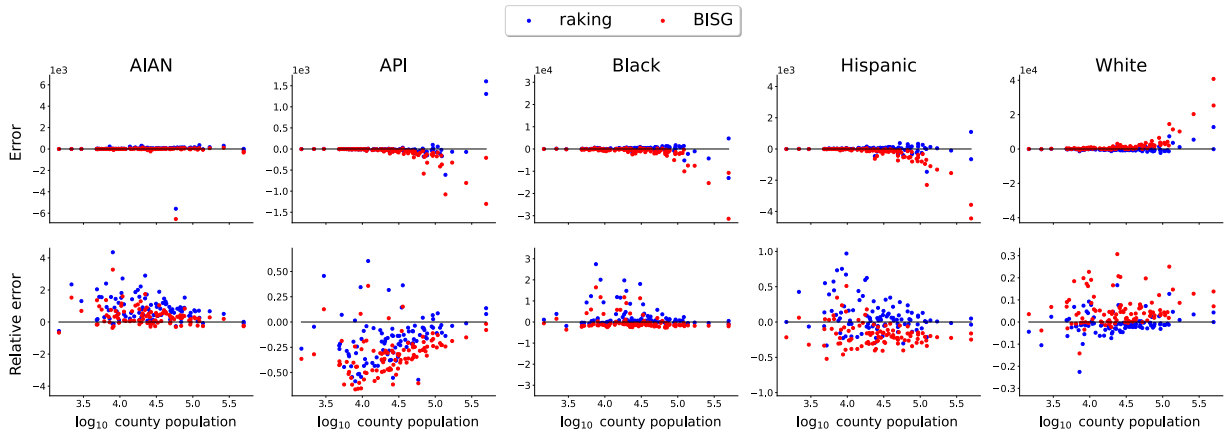
	AIAN	API	Black	Hispanic	White
NC 2010 BISG	0.0016	0.0067	0.0222	0.0051	0.0094
NC 2010 raking	0.0008	0.0017	0.0053	0.0016	0.0060

(e) *North Carolina 2010, subsampled*

	AIAN	API	Black	Hispanic	White
NC 2010 BISG	0.0023	0.0013	0.0210	0.0012	0.0199
NC 2010 raking	0.0021	0.0013	0.0036	0.0012	0.0030

(f) *North Carolina 2010, calibration map*

Table 7: *Kuiper statistics [47] for raking and BISG predictions on Florida (FL) and North Carolina (NC) registered voters using a calibration map and subsampling. Each number corresponds to the total miscalibration over the worst-case interval of predicted probabilities. Here, "worst-case" refers to the interval that makes the absolute value of the total miscalibration as large as possible. Each entry of the table is also the difference between the maximum and minimum cumulative miscalibration as plotted in Figure 7.*



	AIAN	API	Black	Hispanic	White
% of state:	0.8%	1.3%	20.4%	2.9%	72.8%
Rake % of state:	0.8%	1.3%	20.4%	2.9%	72.8%
BISG % of state:	0.7%	1.1%	17.4%	2.2%	77.3%
Rake Mean Error:	0%	0%	0%	0%	0%
BISG Mean Error:	-15%	-15%	-15%	-22%	6%
Rake Mean Abs. Error:	30%	10%	7%	8%	2%
BISG Mean Abs. Error:	25%	15%	16%	22%	6%

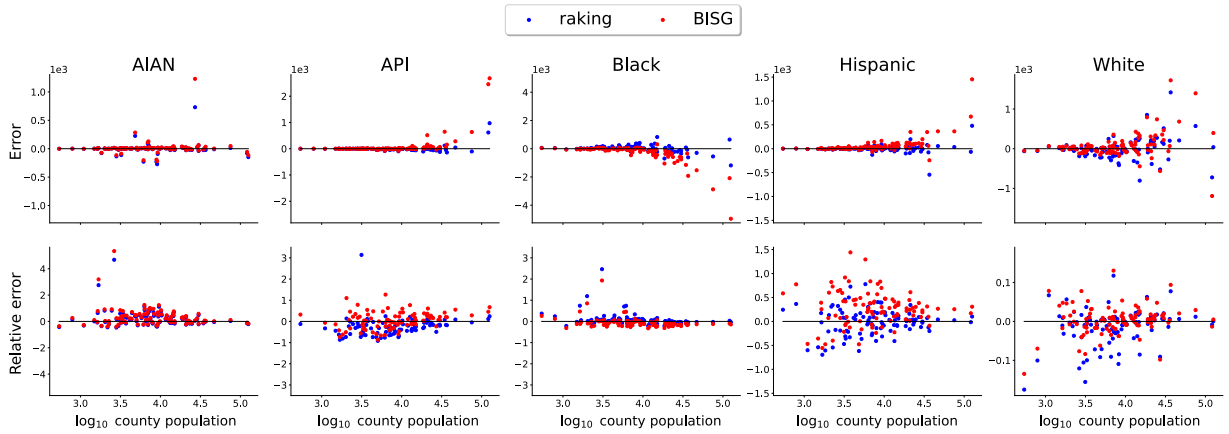
Figure 8: *Errors in subpopulation estimation for registered voters in each county in North Carolina in 2020 for two methods, BISG and raking, using a calibration map. Each dot in the scatterplots represents error of one subpopulation size in one county with BISG or raking. Dots above the horizontal line correspond to overestimating the size of a subpopulation size in one county. Dots below the horizontal line indicate underestimating.*

represent miscalibration with cumulative miscalibration plots (Figure 7), and in Table 7 we report the corresponding Kuiper statistics. The Kuiper statistic is the total miscalibration over the worst-case interval of predicted probabilities, that is, the interval that makes the absolute value of the total miscalibration as large as possible. The Kuiper statistic is also the difference between the maximum and minimum of the cumulative miscalibration plotted in Figure 7.

F. Literature review

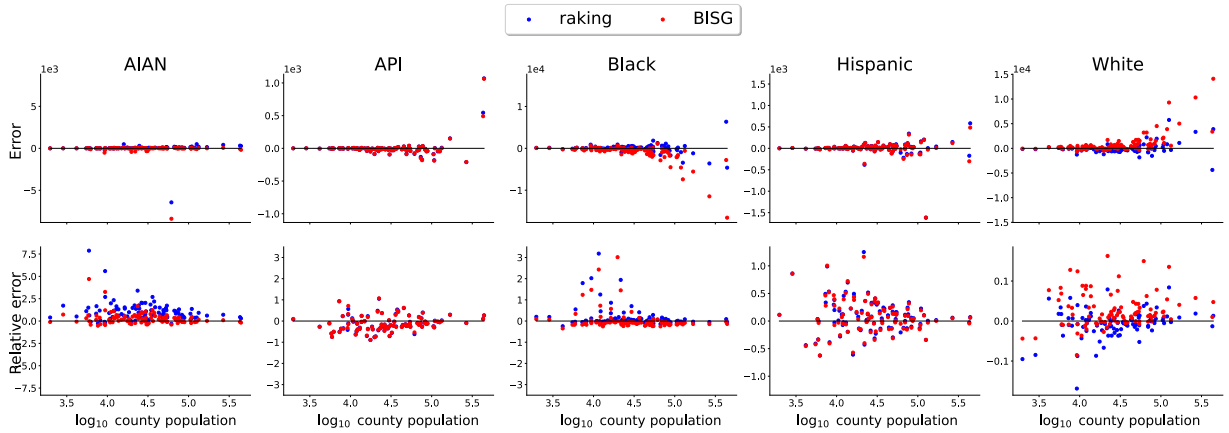
Since its introduction in 2009, BISG has been widely used and has inspired a large body of related work, including algorithm modifications and error analysis. Much of the work on BISG's shortcomings has focused on evaluating accuracy on labeled data sets. For example [8, 49] used a data set of mortgage applications to demonstrate that BISG can overestimate racial disparities. Other studies, such as [19, 20, 35], have evaluated BISG's performance on data sets of registered voters. While these analyses provide a valuable contribution to understanding BISG, their results combine errors from the conditional independence assumption of BISG and differences in the distributions of the test set (registered voters, or mortgage applicants) and the BISG factors (full U.S. population). In Appendix A, we isolated the impact of BISG's conditional independence assumption by fitting and testing BISG on the same labeled data set.

To our knowledge, no prior research has been conducted on directly measuring the impact of BISG's independence assumption on its accuracy. Instead, researchers have relied on indirect evidence, such as using the accuracy of BISG on a labeled data set to demonstrate that the assumption does not result in excessively inaccurate predictions. Various potential sources of inaccuracy in the BISG assumption have been observed in the literature. For example, [35, 36] identify issues in-



	AIAN	API	Black	Hispanic	White
% of state:	**2.2%**	**1.8%**	**20.1%**	**2.4%**	**73.0%**
Rake % of state:	**2.2%**	**1.8%**	**20.1%**	**2.4%**	**73.0%**
BISG % of state:	**2.3%**	**2.4%**	**17.9%**	**2.8%**	**73.6%**
Rake Mean Error:	**0%**	**0%**	**0%**	**0%**	**0%**
BISG Mean Error:	**4%**	**34%**	**-11%**	**21%**	**1%**
Rake Mean Abs. Error:	**12%**	**17%**	**5%**	**11%**	**2%**
BISG Mean Abs. Error:	**14%**	**38%**	**12%**	**24%**	**2%**

Figure 9: *Errors in subpopulation estimation for subsampled registered voters in each county in North Carolina in 2010 for two methods, BISG and raking. Each dot in the scatterplots represents error in one county with BISG or raking. Dots above the horizontal line correspond to overestimating the size of a subpopulation size in one county. Dots below the horizontal line indicate underestimating.*



	AIAN	API	Black	Hispanic	White
% of state:	**0.8%**	**0.5%**	**19.5%**	**1.2%**	**76.7%**
Rake % of state:	**0.8%**	**0.5%**	**19.5%**	**1.2%**	**76.7%**
BISG % of state:	**0.6%**	**0.5%**	**17.4%**	**1.1%**	**78.7%**
Rake Mean Error:	**0%**	**0%**	**0%**	**0%**	**0%**
BISG Mean Error:	**-26%**	**-1%**	**-11%**	**-1%**	**3%**
Rake Mean Abs. Error:	**35%**	**17%**	**6%**	**13%**	**2%**
BISG Mean Abs. Error:	**33%**	**17%**	**12%**	**13%**	**3%**

Figure 10: *Errors in subpopulation estimation for registered voters in each county in North Carolina in 2010 for two methods, BISG and raking, using a calibration map. Each dot in the scatterplots represents error of one subpopulation size in one county with BISG or raking. Dots above the horizontal line correspond to overestimating the size of a subpopulation size in one county. Dots below the horizontal line indicate underestimating.*

cluding (i) within a given race/ethnicity, correlation between surname and wealth combined with clustering of people of similar wealth may lead to correlation between geolocation and surname, (ii) relatives may live in close proximity to each other, and (iii) ethnic groups within the same race/ethnicity (e.g., Indians and Chinese) have distinct surnames and cluster geographically.

Other recent work has focused on how inaccuracy in BISG can impact downstream tasks such as regression analysis. For instance, among other contributions, [14] analyzes the mathematical sources of the overestimation of racial disparities that was observed empirically in [8, 49]. Two authors of [14] build upon their analysis in [38] and observe that disparities are generally unidentifiable with only proxy information. They also propose methods for addressing such issues.

BISG has not only inspired studies on its accuracy; much progress has been made on methodological improvements. These improvements include incorporating features in addition to surname and geolocation [35, 36, 48, 49, 30], the use of Bayesian methods [36], and addressing errors arising from the Census only publishing race/ethnicity distributions of common surnames [36]. There is also a vast literature on name-based prediction of race/ethnicity that does not necessarily use geographic information and has developed largely independently of BISG-related methods. See, for example, [37, 45, 39] for three recent approaches. A comprehensive review of this field can be found in [37], but is beyond the scope of this paper.

The use of known margins to calibrate BISG predictions has previously been used in healthcare applications. For example, in [25] the authors use multinomial logistic regression to transform standard BISG predictions to predictions for members of a national healthcare plan who self-report race/ethnicity. Their multinomial logistic regression uses labeled race information of members of a national healthcare plan as the observation and BISG predictions as the predictors. Applying the fitted logistic transformation to BISG predictions then provides a healthcare-plan specific race/ethnicity prediction. Similar BISG adjustments are used in, for example, [30, 13].

This multinomial logistic correction is similar in spirit to the purpose of raking in this paper. In both cases, after adjusting BISG predictions, the race/ethnicity margin of new predictions matches exactly a known race/ethnicity distribution, in the case of [25], the margin of race/ethnicity of healthcare plan members who self-reported race/ethnicity. This strategy is not directly applicable to the problem we address in this paper since that approach requires labeled race/ethnicity information that is usually missing for registered voters. For example, in states such as New York, the surname by geolocation margin of registered voters is publicly available, but race/ethnicity information of individual registered voters is not available. It is possible to fit a multinomial logistic correction to our predictions by, say, starting with BISG predictions and solving a constrained optimization problem such that the margins of the predictions match the known margins. This can be solved with standard optimization packages. We did not implement this for this paper.[13]

In another healthcare-related BISG improvement, [30] builds a statistical model that incorporates demographic features including self-reported race/ethnicity in order to predict race/ethnicity of Medicare beneficiaries. This approach allows flexible modeling that can relax BISG's independence assumption. As in [25], this approach also relies on labeled race information that is generally unavailable for the registered voter population. Only a handful of states provide any self-identified race/ethnicity, and when that data is provided, proxy methods are generally not required. It's possible that fitting a model in one state and applying it in another can improve accuracy in race/ethnicity predictions. We leave that as an area of future research.

[13] We implemented a similar correction that shifts predictions on the logistic scale, as opposed to raking, which multiplies probabilities. The results were similar to raking and given that raking is a classical and standard tool, we focus on our raking-based method.