

Improved Bayesian Ethnorace Prediction

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Abstract

Quantitative social science research on race and ethnicity can be constrained by the lack of available individual-level data with these markers. In response to this issue, methods have been developed to predict individuals' race and ethnicity using Bayes' rule. Racial distributions from the US Census Surname List are combined with distributions from geolocations, such as Census blocks or zip codes, to yield predicted probabilities of individuals' race and ethnicity. I expand upon existing methods by incorporating information from a nationwide list of first names as well as from residence characteristics. Along with some other adjustments, these improvements lead to substantial gains in predictive performance when validated against official state voter files. The largest of these predictive gains are found for African Americans and Hispanics—groups which existing methods find difficult to predict accurately without fine-grain geolocation information.

Introduction

Research on racial and ethnic disparities in the United States can be constrained by the lack of available individual-level data with these markers (Cascio and Washington 2012; Kuk, Hajnal, and Lajevardi 2020). This is especially true when racial geography is a key aspect of the research design. In these scenarios, researchers are often forced to use aggregate-level data on group proportions, such as county statistics, to draw inferences. But this method is susceptible to the modifiable areal unit problem, whereby statistical bias is introduced due to arbitrary and unequal geographic unit sizes (Fotheringham and Wong 1991). Individual-level

data with ethnoracial categories is also particularly useful for geographic regression discontinuity designs—an increasingly common methodology which typically relies on individually geocoded addresses (Keele and Titiunik 2018; Velez and Newman 2019; Cantoni 2020).

To overcome some of these challenges, in this paper I describe a method for imputing individual ethnorace categories directly. This method uses Bayes’ rule to make predictions by combining information from nationwide distributions of these categories over other characteristics, such as names, geographies, political party identification, among others. My implementation builds off existing methods which use a similar algorithm (Elliott et al. 2009; Imai and Khanna 2016; Voicu 2018). The method described in Imai and Khanna (2016) in particular, and the associated R package `wru`, has become popular in recent studies on race and ethnicity. Its application has been used in work on racial protests and voting patterns (Enos, Kaufman, and Sands 2019), disparities in campaign financing (Grumbach and Sahn 2020; Grumbach, Sahn, and Staszak 2020), and public health issues such as suicide rates (Studdert et al. 2020).

My ethnorace prediction method improves upon Imai and Khanna (2016) in several ways. Whereas their method only takes as inputs distributions over surnames, geolocation, political party, age, and gender, my version adds information from a nationwide list of first names (Tzioumis 2018) as well as address characteristics. Additionally, I incorporate insights from the machine learning literature on the Naive Bayes algorithm. The result of these modifications is a substantial increase in predictive performance compared to Imai and Khanna (2016) in validation tests. These predictive gains are particularly strong in regards to correctly classifying African American and Hispanic individuals—especially in contexts where fine-grain geolocation data are unavailable. My method is available in an easy-to-use R package `bper`.¹

In the next section I will provide some background on the inputs and outputs of my prediction algorithm. Then I will explain the methodology and compare my implementation

¹`bper`: Bayesian Prediction for Ethnicity and Race. <https://github.com/bwilden/bper>

with previous versions. Finally, I will demonstrate the predictive performance of my method when validated against the combined North Carolina and Florida voter file ($n = 21,000,000$).

Data

Outputs

Before discussing the method further, it is important to first define what “predicting ethnicity or race” means. These are categories which, although relatively immutable relative to other identities, do not have universally accepted delineations and meanings (Omi and Winant 2014). I follow the conventions of previous prediction methods by using the US Census Bureau categorizations (Elliott et al. 2009; Imai and Khanna 2016; Voicu 2018). In this framework, individuals can be classified as non-Hispanic White, non-Hispanic Black or African American, non-Hispanic Asian and Pacific Islander, non-Hispanic American Indian and Alaska Native, Hispanic or Latino alone, and non-Hispanic Other Race.² Because Hispanic identity is defined by the Census, and understood commonly, as an ethnicity, rather than a race, I use the term “ethnorace” in this article to refer to any of the previously-mentioned categories.

There are a few benefits to using the Census ethnoracial categorization. These groups capture a common understanding of racial and ethnic groups in the US, and correspond to the groups studied most frequently in social science research. Therefore we are also able to assemble the data sources of these groups’ distributions that serve as inputs to the algorithm. This also facilitates comparison of my method against previous ethnorace prediction methods.³ One downside to using the Census categories, however, is that it obscures substantial

²Non-Hispanic Other Race includes individuals who identify as belonging to two or more race/ethnicities, or mixed race, as well as those who may not identify with the other Census categories.

³Unlike my method, Imai and Khanna (2016) do not include a separate category for American Indian and Alaska Native. In order to create similar comparison groups, I recode all predicted American Indian and Alaska Native individuals as Other Race during the validation exercises. If desired, however, the `bper` package will produce predicted probabilities for the American Indian and Alaska Native category.

heterogeneity that may exist within each group. Within Asian Americans and Latinos, for example, there is considerable variation in terms of national ancestry. Furthermore, the unfortunate necessity of an Other Race category ensures that important sources of diversity are washed over.⁴

Inputs

First Names

The first names list I use comes from Tzioumis (2017). It is drawn from mortgage applicants and contains ethnorace counts in each of the six categories across 4,250 first names. Unlike Census data, which form the basis for much of my other data sources, this list of first names may be unrepresentative of the larger US population. To the extent that first name distributions differ by ethnorace given employment status, for example, this may be a concern. But the predictive benefits from using first name data, as I will demonstrate, likely overwhelms these concerns in most contexts.

Last Names

For my last names data, I use the 2010 Census Surnames List.⁵ This list comes from the 2010 decennial Census and contains over 160,000 common US last names (those occurring 100 or more times). Like the first names list, these data include counts of individuals in each of the six ethnorace categories across each last name.

Geolocation

My ethnorace distributions by geographies come from the 2010 decennial Census, accessed via IPUMS NHGIS.⁶ In descending order of average population, these geographies include

⁴This is hinted at empirically by the method’s abysmal predictive performance for the Other Race category.

⁵https://www.census.gov/topics/population/genealogy/data/2010_surnames.html

⁶Steven Manson, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. IPUMS National Historical Geographic Information System: Version 15.0 [dataset]. Minneapolis, MN: IPUMS.

state, county, Census place, ZIP code, and Census block. Predictions tend to improve with more precise levels of geography. With this in mind, my implementation automatically matches each individual to the most fine-grain level of geography available.

Method

Validation

Conclusion

cite list:

methods:

- (Voicu 2018)
- (Tzioumis 2018)
- (Shah and Davis 2017)
- (Imai and Khanna 2016)
- (Elliott et al. 2009)
- (Crabtree and Chykina 2018) (independence assumption)
- (Lauderdale and Kestenbaum 2000) (asian surnames)

naive bayes:

- (Rish 2001)
- (Lewis 1998)

- (Domingos and Pazzani 1997)

applications:

- (Velez and Newman 2019) (use NC)
- (Studdert et al. 2020) (medical study)
- (Kuk, Hajnal, and Lajevardi 2020) (aggregate)
- (Cascio and Washington 2012) (aggregate)
- (Cantoni 2020) (RDD)
- (Hersh and Nall 2016) (catalist)
- (Ghitza and Gelman, n.d.) (catalist)
- (Grumbach and Sahn 2020)
- (Grumbach, Sahn, and Staszak 2020)
- (Fraga 2018) (turnout)
- (Enos, Kaufman, and Sands 2019) (protests and voting)
- (Enos 2016) (racial threat)

race:

- (Omi and Winant 2014)

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