Predicting Race and Ethnicity From Sequence of Characters in a Name*

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Abstract

To answer questions about racial inequality, we often need the ability to reliably infer the race of a person based on their name. The census bureau provides common last names and proportion of people belonging to different races who have the last name. But there is more information in the first names. To estimate the relationship between full names and race, we exploit the Florida voting registration data, and the Wikipedia data collected by Skiena and colleagues, to predict race and ethnicity using Long Short Term Memory Networks. Our out of sample precision and recall on Florida Voter Registration data is .83 and .84 respectively. This compares to OOS recall of .78 and .79 for last name only models. Commensurate numbers for Wikipedia data are .72 and .73 and .65 and .65. We provide a Python package to easily predict the race and ethnicity of names. We apply our method to the campaign finance data to estimate the share of donations made by people of various racial groups and investigate whether people are more likely to contribute to co-ethnics conditional on ideology.

*Data and scripts behind the analysis presented here can be downloaded at: http://github.com/appeler/ethnicolr.

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How often are people of different races and ethnicites covered in the news? How often do African Americans contribute to political campaigns? To answer these questions and questions like these, we often need a way to infer race and ethnicity from names. Given the important questions that could be answered if we had a reliable way to do such mapping, a variety of attempts have been made to infer race from names. For instance, recently Imai and Khanna (2016) presented a way to infer ethnicity from last names by using geographic data along with the census data. In this paper, we contribute to this broad literature.

Poor African Americans have distinctive first names (Bertrand and Mullainathan 2004).

We exploit the US census data, the Florida voting registration data (Sood 2017), and the Wikipedia data collected by Skiena and colleagues (Ambekar et al. 2009) to learn a model between sequence of characters in a name and race and ethnicity. We use Long Short Term Memory to learn this association. The granularity at which we predict the race depends on the dataset. For instance, in Ambekar et al. (2009) data, the race and ethnicity is coded fairly granularly at a geogrpahic ethnic group level, while the census data we use in the model, the we only categorize between Non-Hispanic Whites, Non-Hispanic Blacks, Asians, and Hispanics. Our out of sample precision and recall is .83 and .84 respectively. This compares to OOS recall of .78 and .79 for last name only models. We also provide a Python package to easily predict the race and ethnicity of names. Lastly, we apply our method to the campaign finance data to estimate the share of donations made by people of various racial groups and investigate whether people are more likely to contribute to co-ethnics conditional on ideology.

Method

If you picked a random individual with last name Smith from the US in 2010 and asked us to guess this person's race (measured as crudely as by the census), the best guess would be based on what is available from the aggregated Census file. It is the Bayes Optimal Solution. So what good are last name only predictive models for? A few things. If you want to impute ethnicity at a more granular level, guess the race of people in different years (than when the census was conducted if some assumptions hold), guess the race of people in different countries (again if some assumptions hold), when names are slightly different (again with some assumptions), etc. The big benefit comes from when both the first name and last name is known.

Data, Model, and Validation

The Census Bureau provides frequency of all surnames occurring 100 or more times for the 2000 and 2010 census. Technical details of how the 2000 and 2010 data were collected can be found on the census website. The Wikipedia data were originally collected by a team lead by Steven Skiena as part of the project to build a classifier for race and ethnicity based on names. The team scraped Wikipedia to produce a novel database of over 140k name–race associations. For details of the how the data was collected, see Ambekar et al. (2009). The third dataset is the Florida Voting Registration data for the year 2017. The Florida Voting Registration data has information about voter's race.

Table 1: Registered Voters in Florida by Race.

Race	Count
asian	253,808
hispanic	2,179,106
nh black	1,853,690
nh white	8,757,268

We can use the Wikipedia data and the Florida Voting Registration data as is but the Census data needs to be transformed before being used. The dataset that the Census Bureau issues aggregates data for each last name and provides percentage of people with the last name who are Black, White, Asian, Hispanic, etc. Given some names are more common than others (Smith is the last name of 2,376,206 Americans), and given our interest in modeling the population distribution, we take a weighted random sample from this data with weight equal to how common the last name is in the population. Next, we assign race to name roughly in proportion to how the name is distributed across the racial groups. We assign floor of pctwhite as whites, floor of pctblacks as blacks etc. And we lose the one or two or few observations as we are using floor. We use this as the final dataset.

For our full name model, we concatenate the last name and first name and capitalize the first character of all the words. We next split the name into two character chunks (bi-chars). For instance, Smith becomes Sm, mi, it, and th. We then remove infrequent bi-chars (occurring less than 3 times in the data) and very frequent bi-chars (occurring more than 30% in the dataset). We use the remaining bi-chars as our vocabulary. We pad the sequences so that they are the same size. And we use 20 as the window size for the last name only model and 25 for the full name model. Lastly, we split the data randomly into train (80%) and test (20%). We next train a LSTM model.

The table 2 presents some metrics that shed light on how well we did with the last name only model in predicting race OOS. The table 3 presents some metrics that shed light on how well we did with the full name only model in predicting race OOS.

Given poor African Americans have distinctive first names, the largest improvements in recall that we see are among African American names. We go from a poor recall of .13 for African American names in the last name model to a still poor but much improved recall of .45 with the full name model.

Table 2: Performance of the Last Name LSTM Model on the Florida Voter Registration Data.

race	precision	recall	f1-score	support
asian	0.77	0.35	0.48	50,762
hispanic	0.80	0.81	0.80	435,821
nh black	0.68	0.13	0.22	370,738
nh white	0.80	0.94	0.86	1,751,454
avg / total	0.78	0.79	0.75	2608775

Table 3: Performance of the Full Name LSTM Model on the Florida Voter Registration Data.

race	precision	recall	f1-score	support
asian	0.77	0.45	0.56	50,762
hispanic	0.83	0.84	0.83	435,821
nh black	0.74	0.45	0.56	370,738
nh white	0.86	0.93	0.89	1,751,454
avg / total	0.83	0.84	0.83	2608775

Application

To illustrate how the package can be used, we impute the race of the campaign contributors recorded by FEC for the years 2000 and 2010 using the DIME data (Bonica 2017) and tally campaign contributions by race. In 2000, nearly 96% of the contributions were made by whites and just .16% of the contributions were made by blacks (see Table 4). In 2010, things didn't look a lot different, with nearly 94% of the contributions being made by whites and just .22% made by blacks.

Table 4: Proportion of Donors to Political Campaigns in 2000 and 2010 by Race.

Race	2000	2010
asian	1.43%	2.14%
black	0.16%	.22%
hispanic	2.57%	4.04%
white	95.84%	93.60%

Discussion

We exploit a novel source of data—voter registration data—to learn a model between sequences of characters in a name and race or ethnicity. Given poor African Americans tend to have distinctive first names, the biggest advantage in using the full name model is in our ability to detect African American names. We use the model to infer the race of contributors in the DIME data and find that African Americans are less than a quarter percent of the donors. As we note, we also provide a Python package that exposes the models: https://github.com/appeler/ethnicolr/.

The limitations of using the voter registration data are obvious. Not everyone is registered to vote, and blacks and hispanics are especially likely to not be registered to vote (Ansolabehere and Hersh 2011). If the names of those who are not on the voter registration file are systematically different from those who are, we are likely somewhat optimistic in our accuracy metrics. Another concern with using data from a single state is that the pattern of names in a single state are different from names given in other states. It is a very reasonable concern. We could overcome it by combining census last name models with state voter registration data models but more research is needed to see how well we can do.

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