

Gender and Race in Carolina Digital Repository Content Methodology Review

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Introduction

In 2021, I conducted a [review of subject area, gender and race representation](#) in three Carolina Digital Repository (CDR) projects. The goal of the review was to determine if the content produced by the three projects were representative of the demographics of the University of North Carolina at Chapel Hill (UNC-CH). I used a publicly available, widely distributed list of faculty members who self-identified as Black, indigenous or a person of color and compared the list to CDR deposits. Also, I used a frequently cited API tool to determine author gender, based on recommendations from several bibliometrics studies.

At the end of the review, I recommended further research and reflection on ways to identify gender and race of CDR authors in an accurate and ethical manner. This report represents the first step in that reflection, and it will be an ongoing and iterative process. For this assessment, I first looked at studies which estimated race and/or gender composition of their subjects. I then categorized the methodologies to determine the most used. In this follow-up review, I will report on the results of my investigation into alternate methods to identify gender and race of authors, provide an evaluation of the previous study based on my findings and provide a recommendation for future work.

Gender

I looked at 23 studies in a variety of fields which estimated the gender of subjects based on their names. For each study, I locate the methodology section and noted the methods by which the study authors determined gender. The primary methodologies are grouped in the table below. Articles which use multiple methods have been grouped by the primary method.

Method	Number of Studies
API (e.g. gender API, genderize.io etc.)	15
Photo	2
Pronouns	5
Salutation	1

Most studies used an API tool to estimate gender. These tools rely on a large dataset of given names matched to gender. Datasets can be created from publicly available data sources, such as the United States Social Security Administration. The API will match the user input to the dataset and return a result of “male”, “female” or “unknown” with a measure of confidence expressed as a percentage. Typically, the study authors determined a threshold percentage by which they assume the predictions to be accurate, which ranged from 70% to over 90%. Matches lower than the threshold percentage are either discarded or validated using another method.

Several studies noted the drawbacks of API-based tools:

1. They represent a binary view of gender and are therefore exclusionary to non-binary individuals.
2. The data sources are highly dependent on nationality. Data sources can lack coverage, particularly for East Asian names in Western datasets. Additionally, names can be associated with different genders depending on nationality (e.g., Andrea is a common female name in the United States, but a common male name in Italy.)
3. They do not predict gender neutral names accurately.

The second most popular method of gender assessment is preferred pronouns. In this method, researchers performed web searches for subjects’ names to identify the pronouns that they used on social media and departmental websites. This method assumes that the subjects have a web or social media presence, which may not be true for subjects in historic datasets. Additionally, it assumes that the subject’s publicly used pronouns align with their true gender identity.

Two studies used photographs as the primary method to assess gender. The researchers used publicly available websites such as department web pages to obtain photographs of the subjects and assessed their gender presentation. This method assumes that photographs are available for every subject and that the subject’s public gender presentation reflects their true gender. Additionally, the method relies on the researcher’s preconceptions of gender presentation, which could introduce bias.

Finally, one study relied on gendered salutations such as “Mr.”, “Mrs.”, “Miss” or “Ms.” As with the previous two methods, this method assumes that the subject’s publicly used salutation aligns with their true gender. This method also has limited utility in an academic environment where the gender-neutral salutations “Dr.” or “Prof.” are common.

Race

I looked at 15 studies in a variety of fields which assessed the racial makeup of subjects. For each study, I located the methodology section and noted the methods by which the study authors determined race. The primary methodologies are grouped in the table below. Articles which use multiple methods have been grouped by the primary method.

Method	Number of Studies
Self-identified	9
Photo	2
External dataset	2
Unknown	2

Most studies used self-identification to determine race, in which the subjects indicated their race based on pre-written categories on a questionnaire or similar. This method assumes that a questionnaire can be viably administered, and that the subject's racial identity falls neatly into the provided categories.

Two studies used photos to determine the race of their subjects. As with the gender assessment, this method assumes that photographs will be available for all subjects and relies on the assessor's preconceptions of race, which may be biased.

An additional two studies used external datasets which listed the subjects' race but did not identify how the external datasets assessed race to determine those categories. Finally, two studies indicated that race was assessed, but did not provide explicit information about their data gathering or assessment process.

Recommendations

Gender

An API-based approach was by far the most used method for assessing gender, which aligns with my methodology in the first round of assessment. However, the drawbacks noted in the section above are significant and need to be acknowledged when performing an assessment. Furthermore, when an API-based approach is used, it is best to set the threshold percentage high and to use an alternate approach to manage outliers. However, using this approach on a large dataset such as the CDR's dataset will generate a good deal of manual work that will need to be managed and accounted for.

An approach based on the subject's preferred pronouns is preferable to an API-based approach as it reflects the subject's gender identity. Given the large size and age of the dataset used for the CDR analysis, this method will eliminate many older articles since authors of older articles will be less likely to have a current web or social media presence. It may be useful to analyze a sample set to establish a baseline and to assess potential issues.

Race

Self-identification was by far the most utilized method to assess race. This aligns with the methodology of the previous assessment, since the subjects were provided the option to self-identify as a member of a racial minority group. Since the CDR does not require users to provide demographic information upon deposit and we have no plans to do so, the previous methodology is the best way to determine race of depositors. However, the list only includes faculty who chose to self-identify as a member of a minority group and does not reflect a comprehensive view of the university. Due to de-identification, it is unlikely that an external dataset from university HR or research office would provide enough information for further assessment. Assessment based on photographs would introduce bias and would be ethically dubious at best.

Therefore, it may be advisable to shift focus from spotlighting work authored by BIPOC authors to a topic-based approach. In this approach, I would identify keywords and research topics relating to

minority populations and verify that eligible research was available in the CDR. One such approach was piloted at Virginia Tech, in which the researchers compiled a controlled vocabulary describing minority groups and used the terms to search the university's website and institutional repository.¹ These searches provided a basis of comparison to determine if research on a particular subject was being performed at the university and if so, whether its outputs were deposited in the institutional repository.

We hope that the approaches above will be a first step toward broadening the subject area, race, and gender focus of the CDR, which will bring the CDR more in line with UNC Libraries' Reckoning Initiative. We will continue to assess our progress and publicly publish updates on a yearly basis, as we have done with the Content Liberation projects and the CDR platform updates.

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Gender

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