Emancipating data science for Black and Indigenous students via liberatory datasets and curricula

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Abstract

Despite findings highlighting the severe underrepresentation of women and minoritized groups in data science, most scholarly research has focused on new methodologies, tools, and algorithms as opposed to *who* data scientists are or *how* they learn their craft. This paper proposes that increased representation in data science can be achieved via advancing the curation of datasets and pedagogies that empower Black, Indigenous, and other minoritized people of color to enter the field. This work contributes to our understanding of the obstacles facing minoritized students in the classroom and solutions to mitigate their marginalization.

Keywords

emancipation, data harms, data science, liberatory pedagogy, curricula

Introduction

The data science profession is currently dominated by white and Asian males (Harnham Report, 2021; Duranton, *et al,* 2020). In fact, just 27% of data scientists, defined as individuals who code, collaborate, and communicate by transforming data into insights using techniques in statistics, analytics, and machine learning (Ho *et al,* 2019) in the U.S. identify as women; 6% as Latinx and 3% as Black, (Harnham Report, 2021) despite representing 51%, 19% and 12% of the population respectively (US Census, 2020). This pattern is particularly concerning, as according to the U.S. Department of Labor, data science occupations are expected to rise +Δ 25.9% and outpace projections of every other computer occupation (+Δ 12.7%) or occupations overall (+Δ 5.2%) (Rieley, 2018). Furthermore, despite the rapid growth in data talent Brahm *et al*, 2019), the supply of data workers is not expected to keep up with demand (Miller and Hughes, 2017). Therefore, strengthening workforce capacity in data science, defined as the ecosystem dedicated to the systematic collection, management, analysis, visualization, explanation, and preservation of structured and unstructured data (Marshall and Grier, 2019) will require attracting more Black, Indigenous, and other marginalized people of color into the data workforce.

Background

Race/ethnicity and gender workforce disparities are not new. The marginalization and exclusion of Black, Latinx and Indigenous/Native people remain a problem in the science, technology, engineering/computer science and mathematics (STEM) fields. According to the 2018 Survey of Earned Doctorates, Latinx students were awarded 6.7% of STEM doctoral degrees, Black students earned 4.9%, and American Indian/Alaska Native students earned just 0.2 % (NSF, 2019). In computing, women's overall share of U.S. undergraduate computing degrees has dropped from 28.5% in 1995 to 18.1% in 2014; and the trends for women of color in computing are more alarming, as their completion rates either flat-lined at 1.75% (in the case of Latinx women) or dropped from 5.10% to 2.61% in the case of Black women over that same timeframe (Payton and Berki, 2019). As of 2016, Black and Latinx women combined made up just 4.4% of U.S. undergraduate computing degrees (NSF, 2017). This race/ethnicity and gender underrepresentation of minoritized groups in STEM has been attributed to pervasive problems in recruitment (i.e., motivations to enter) and retention (i.e., intentions to remain) of minoritized students in higher education (Fox, 2009; Drury, Siy and Cheryan 2011; Smith-Doerr, Alegria and Sacco 2017). Data science, like its core disciplinary predecessors (computer science, information systems, mathematics, and statistics), suffers from a critical lack of race/ethnicity and gender diversity. Therefore, meeting the nation's need for a data workforce that is reflective of its populace requires new ways of educating and training data professionals from minoritized backgrounds. Furthermore, if these patterns persist, data harms (preliminarily defined as the adverse effects caused by uses of data that may impair, injure, or set back a person, entity, or society's interests) (Redden, Brand and Terzieva 2020) resulting from a homogeneous (i.e., white male) data workforce will reinforce as opposed to resolve structural racist practices that continue to marginalize Black and indigenous people in the U.S.

Increasing the U.S. data workforce is likely to remain a top priority over the coming decades. This creates a unique opportunity for non-STEM and minoritized students to find career paths in data work (especially data visualization and data journalism, which align nicely with topics of interest to humanities students (Manovich, 2015). Given that most minoritized students graduate in non-STEM majors (see Figure 1), this population represents a large untapped resource for the future data science workforce. Through exposure to data professionals and use of datasets that reflect the unique

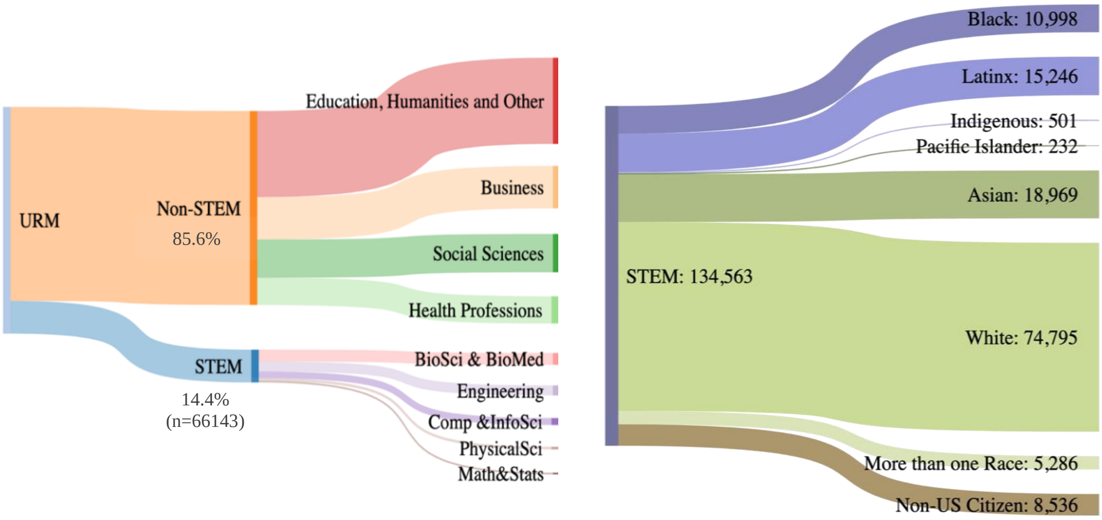

FIG 1. Image by Author. Sankey diagrams of 2017 Bachelor's Degree Completions by Discipline of Undergraduate minoritized Students overall (LEFT) and in STEM (RIGHT) (Source: U.S. Department of Education NCES IPEDS database.)

historical and varied experiences of Black, Indigenous, and other minoritized people of color, we can facilitate inclusive growth in the U.S. data workforce. Therefore, this paper aims to offer strategies for identifying more affirming and relevant datasets and exemplary data scientists that cater to the wants and needs of non-STEM minoritized populations.

Facilitating a racial equity orientation in data science

The unprecedented influence of data science tools and technologies on our social institutions (Benjamin, 2019) coupled with a pervasive lack of diversity in the sciences and data science in particular, limits the range of perspectives (Page, 2008) needed to address the sociotechnical complexities of "biased" (i.e., harms associated with the deployment of models that are trained on datasets that reflect broader structural inequalities) datasets and analytical processes. At present, outcomes of data science workflows lead to a profound impact on the public and underrepresented and minoritized groups in particular. Biased datasets and analytical processes have furthered inequities in judicial systems, i.e., recidivism risk (O'Neil, 2016; Flores, Bechtel and Lowenkamp, 2016; Dressel and Farid, 2018; Angwin *et al*, 2016) search engine outputs (Noble, 2018), and facial recognition (Buolamwini and Gebru, 2018) among others. Joy Buolamwini and Timnit Gebru's research exposed data harms caused by facial recognition software that disproportionately misclassified darker-skinned female faces (34.7% error rate) at a rate 43 times higher than that of lighter-skinned males (.8% error rate). Systems like these are used in concert with massive law-enforcement databases with images of over 117 million U.S. adults (over half the entire U.S. population) for police and government surveillance, leading to the false identification of innocent suspects (Garvie, Bedoya and Frankle, 2019).

In addition to economic and data harms justifications for increasing the diversity of the data workforce, a smaller yet growing segment of the academic literature explores the substantive contributions of minoritized groups to the U.S. workforce. For example, evidence suggests that minoritized students of color (1) care more about using their work to assist others (Miller *et al*, 2000), (2) are more likely to endorse communal goals (Seymour and Hewitt, 1994), (3) emphasize collectivist values, (Smith *et al*, 2014) and (4) address issues of social justice (Allen *et al,* 2015). The equity ethic framework, defined as a "principled concern for social justice and for the well-being of people who are suffering from various inequities," (McGee and Bentley, 2017) places these motivating forces at the center of the underrepresented minoritized STEM student experience. Specifically, an equity ethic is understood as a psychological attribute that is characterized by the degree to which an individual's social justice concerns are developed and ultimately acted upon (Naphan-Kingery *et al*, 2019). This line of research centers on actions stemming from a social justice orientation, which entails helping others for the purpose of reducing social inequalities. Findings suggest that students from historically marginalized backgrounds in engineering and computer science are "likely to develop an equity ethic because they are likely to experience oppression and discrimination and to recognize inequity and social suffering in similarly situated groups" (ibid., p. 3). In data work, an equity ethic would express itself in the form of proactively using statistics and machine learning to address social problems (i.e., human trafficking, algorithmic bias, etc.) that disproportionately affect marginalized communities. The author refers to these data scientists with an equity ethic orientation as emancipatory (Monroe-White, 2021).

Emancipatory data science is defined as data work that frees members of marginalized communities from being the 'object' to the 'subject' of data science framings and where decisions regarding why, how, what, when, and where data are collected, managed, analyzed, interpreted and communicated are maintained by and for members of minoritized, marginalized and vulnerable communities (Monroe-White, 2021). Emancipatory data science matters, because for members of marginalized, minoritized, and vulnerable communities, *who* provides the service (e.g., medicine, education, finance, housing, etc.) affects *how* the service is delivered (Gershenson *et al*, 2018; Alsan, Garrick and Graziani, 2019; Steenbarger, 2020). The resulting impact is that having same race doctors and teachers lead to greater standards of care and improved educational outcomes for members of these groups. Knowing this; however, requires a reflexive perspective that until recently was missing from the data science academic literature. As an applied social science, majoritarian data science (and data scientists) tend to neglect the study of their own social conditions and normative behaviors (Merton, 1949) in favor of examining the data of others. However, as more institutions develop data science programs to meet growing student and industry demand, the opportunity to address inequities earlier as informed by empirical evidence becomes even more pressing (Kelly, 2005). Furthermore, unless intentionally and actively corrected, these data science programs will continue to reinforce systemic and structural biases that have disproportionately marginalized students from these fields (Monroe-White, Marshall and Contreras-Palacios, 2021; 2022). By leveraging lessons from culturally-relevant pedagogy, data curators (i.e., those responsible for creating, organizing and maintaining data sets) and data science instructors can identify and provide increased access to 1) datasets established about Black and Indigenous peoples and 2) tools that facilitate minoritized student adoption and interaction. Ultimately, the aim of these efforts would be to make data science more inclusive and affirming for non-STEM (i.e., business, humanities, education etc.) members of Black and Indigenous communities thereby increasing capacity within the U.S. data workforce, and minimizing data harms caused by anti-black, anti-indigenous datasets and algorithmic models utilizing what Zuberi and Bonilla-Silva term "White logic" (2008). That is, the context in which White supremacy has defined the techniques and processes employed to analyze data as well as the reasoning used by researchers to understand society. In the world of data science, this requires a critical reassessment of the logic behind and implications of data science processes.

Liberatory data science pedagogical framework

There is an increasing need for racially relevant and responsive teaching in university settings. The Ladson-Billings model of culturally relevant pedagogy has been applied to STEM courses to promote a more inclusive culture for minoritized students (Larnell, *et al*, 2016; Johnson and Elliott, 2020). One component of this three-part model requires cultural competence or creating a classroom culture where students feel they can be themselves. Being culturally competent; however, often involves changes to the curriculum in ways that incorporate students' cultural knowledge, as in a data analytics course where students analyze and visualize data related to racial justice. This helps "students recognize and honor their own cultural beliefs and practices while acquiring access to the wider culture" (Ladson-Billings, 2008) Learning modules would teach students fundamental and in-demand data science software (i.e., R, Python, SQL, Tableau etc.) and skills using culturally relevant datasets (see Figures 2a & 2b) that are widely accessible by faculty and students alike.

A liberatory data science curriculum would include prepared datasets and guidance on analytical processes (i.e., data acquisition, preprocessing, modeling, visualization, and interpretation) in a way that promotes student voice and sense of belonging, highlights the work of historical and contemporary data scientists from non-dominant cultures, and encourage students to contribute their own cultural knowledge through class assignments and activities. For example, the following Black and Indigenous resources are publicly available and readily accessible to data science instructors.

1. Native Land: https://native-land.ca/
2. Racial Terror Lynchings: https://lynchinginamerica.eji.org/explore
3. Ida B. Wells Just Data Lab: https://www.thejustdatalab.com/
4. Slave Voyages: https://www.slavevoyages.org/

Learning modules that leverage datasets and data visualization resources like these can be made available to a broad audience via open access platforms (e.g., GitHub) (Banerjee, 2015) and serve as training tools for data science educators by leveraging best practices in culturally relevant instructional design. Racial justice would also be of particular importance to members of minoritized groups and other marginalized communities, including those pertaining to racial activism (i.e., location of Black Lives Matter protests) and racial injustice (i.e., anti-Black police shootings), economic empowerment (i.e., historical significance of Black wall street) and economic disparities (i.e., White flight and gentrification), and public health (e.g., COVID-19 rates within URM communities) (Benjamin, 2019).

For example, a Black undergraduate history, anthropology, theology or linguistics student, after taking an introductory data science course employing a liberatory data science framework, may as an end-of-semester project choose to create an interactive map of the transatlantic slave trade to examine survival rates by ship, country of origin and destination (see Figures 2a and 2b). This would be particularly meaningful as W.E.B. Dubois (the first formerly trained Black sociologist in the United States) created such a map *by hand* working with students at the Atlanta University Center in 1900.

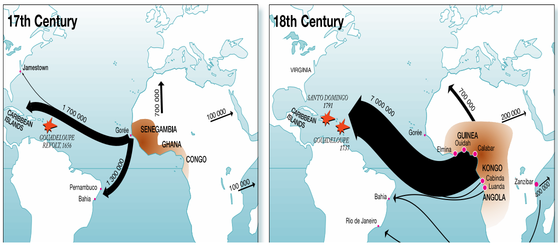

FIG 2a "The Slave Route" (Source: UNESCO 2006)

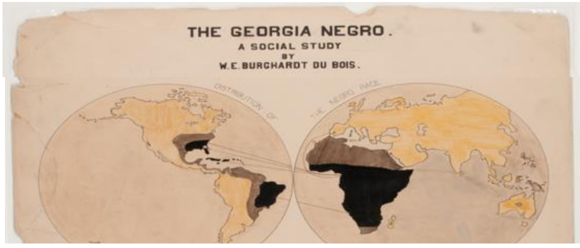

FIG 2b "The Georgia Negro" (Source: W.E.B. Dubois, 1900)

Adding additional levels of interactivity would allow the user to; for example, identify particularly treacherous travel routes, and offer data-driven explanations for the variety of cultural, religious and linguistic innovations produced by descendants of survivors throughout the America's including: 1) the Gullah-Geechee whose creolized language, religion and culture is practiced in the coastal areas and sea islands of the U.S can trace its origins to Sierra-Leone and Benin; 2) Haitian creole (kreyòl) which combines elements of the French language with Central-African (i.e., Kongolese), West-African (i.e., Akan Twi) religious and cultural practices, and; 3) Palenque, which combines Kongolese and Spanish and is spoken by Afro-Colombian descendants of escaped slaves (e.g., Maroons or Cimarrónes) in the Pacific and northwest regions of Colombia, South America.

Adding racially relevant and global dimensions to data science educational curricula is both empowering and intellectually liberating for minoritized students, as it humanizes the gruesome realities while simultaneously respecting the diasporic experiences of descendants. Students in the liberal arts (i.e., history, anthropology, English, etc.), are then motivated to learn data science by exploring topics of personal relevance and academic interest. By making data accessible, analyzable, and interpretable to non-STEM students and leveraging datasets to teach data science (and close cousins such as data journalism, data mining, data visualization, etc.) programs can provide non-STEM minoritized students with an opportunity to explore phenomena that are academically relevant and personally meaningful, thereby exposing and attracting a broader, more diverse segment of the population data careers (Jackson *et al*, 2019).

Conclusion

Infusing Black and Indigenous history and liberatory pedagogy into data science education empowers educators to create more affirming and inclusive pathways into the field for minoritized scholars. This could ultimately lead to the mitigation of data harms by having a more diverse and inclusive data science workforce capable of identifying and challenging biased datasets and algorithms pre-deployment. As providers, curators and instructors of data best practices and systems, we are responsible for preparing members of the data science workforce to intelligently contend with the socio-technical complexities of their work, create liberatory data science pedagogy and curricula (Castillo-Montoya, Abreu and Abad, 2019; Johnson and Elliott, 2020) and advocate for the use of data to empower Black, Indigenous and marginalized people of color.

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Endnotes

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