Using a Text Mining Assignment as an Intervention to Promote Student Engagement With DEI Issues

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ABSTRACT

The goal of the Partnership For Equity project is to build inclusive computing and engineering professional mindsets, which describes attitudes and identities of students who value knowledge in both technical and diversity, equity, and inclusion (DEI) areas of computer science. In this paper we present results from an intervention we piloted in a text mining special topics class. This intervention is directly applicable to any data mining class. Students applied naive Bayes classification to a survey result dataset and classified responses as "technical" or "equity", where technical meant the survey question response was focused on technical issues, whereas "equity" meant the response was focused on DEI issues. The survey data came from another course where students watched Ms. Joy Buolamwini's 2016 "How I'm fighting bias in algorithms" TedX talk and then answered several survey questions about the talk. In our text mining course students were first asked to watch the same TedX talk and answer several of the same survey questions. Their answers were added to the original data set. Students were then asked to apply naive Bayes classification to the combined survey results for one question. At the end of the course students took an end of class survey and answered more open-ended questions about whether the assignment influenced their thinking about DEI in computing. Results from this intervention indicate that including a DEI focus in technical programming assignments can positively impact students' views on the importance of DEI and contribute to the development of computing and engineering professional mindsets.

CCS CONCEPTS

• **Social and professional topics** → **Computer science education**; **Race and ethnicity**; *Computer engineering education*; • **Computing methodologies** → Supervised learning by classification.

KEYWORDS

inclusive identities; race and gender; computer science education; text mining

SIGCSE '21, March 13–20, 2021, Virtual Event, USA

ACM ISBN 978-1-4503-8062-1/21/03…$15.00
https://doi.org/10.1145/3408877.3432557

ACM Reference Format:
Scott T. Leutenegger and Christina H. Paguyo. 2021. Using a Text Mining Assignment as an Intervention to Promote Student Engagement With DEI Issues. In *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education (SIGCSE '21), March 13–20, 2021, Virtual Event, USA.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3408877.3432557

1 INTRODUCTION

The Partnership For Equity project is a multi-university, five-year project funded by the National Science Foundation (NSF) with the aim of building inclusive professional mindsets in engineers and computer scientists. We conceptualize inclusive professional mindsets as attitudes and identities of students who value knowledge in both the technical and diversity, equity, and inclusion (DEI) areas in computer science and engineering. Since students who enroll in computer science classes rarely, if ever, expect to discuss issues of inequity, racism and sexism in their technical courses, we introduce students to DEI through assignments that require engagement with DEI through the lens of their academic disciplines. Our goal is to help students build a more inclusive professional identity. In this paper we describe interventions from a spring quarter 2020 computer science special topics class on text mining. There were 15 students who enrolled in and completed the course, 8 of whom were female and/or minoritized students. To help students see a relationship between technical content and DEI, they were asked to use naive Bayes, a data mining classification technique, to classify student DEI survey responses. In order to do the project the students needed to understand the data set which was created by students viewing Ms. Boulamwini's 2016 "How I'm fighting bias in algorithms" TedX talk [4] and answer several survey questions about the applicability of the issues in the talk to their academic discipline. Actively engaging with material and creating relationships between what students learn in class and how it applies to their personal lives results in deeper and more robust learning [10]. Thus, we believe this approach offers an opportunity to meaningfully engage with equity and inclusion issues within the context of computer science in a meaningful way. While we have embedded this intervention into a text mining class, it should be possible to use the same or a similar intervention in any machine learning course and hence has significant applicability within computer science.

The remainder of this paper is organized as follows. Section 2 discusses some relevant background within which our work is situated. Section 3 describes in detail our interventions. Section 4 presents our results. We conclude in section 5.

2 BACKGROUND

This specific work is part of our larger multi-university, multi-year, and multi-disciplinary Partnership For Equity project [2, 17]. The project aims to embed concepts of DEI throughout Engineering and Computer Science curricula so that students see the relationship between issues of equity and the engineering and computing professions. Ultimately, we hope our students develop fluency in technical content and DEI so they graduate with robust interpersonal skills, stronger teamwork abilities, and critical understandings of how they can professionally and personally create a more just society. This work exemplifies one aspect of the overall project: infusing DEI related topics into technical classes that guide students to grapple with DEI issues. The confluence of COVID-19, racial reckonings, climate change, and socio-political turmoil compels us to address these issues in higher education. If we turn a blind eye to this convergence of pandemics, we reify the same systemic inequities education aims to dismantle.

While our general goal aligns with many efforts focused on broadening participation in computing as referenced in recent papers, panels and working groups [1, 3, 5–7, 9, 11, 16, 18, 19, 21, 23, 27], the specific focus of this work is to broaden DEI awareness and build inclusive professional mindsets of all undergraduate computer science and engineering majors. We posit that building inclusive professional mindsets can impact computer science identities more broadly. A framework for understanding K12 computer science identities is presented in [28]. To complement initiatives that support students from historically disenfranchised communities, our project aims to shift student mindsets and transform computer science culture so that all students can experience success, affirmation, and inclusion [26]. A recent paper [25] presenting study results focused on minoritized youth in AP CSP courses included a concluding recommendation that "CS classrooms should openly discuss issues of discrimination in the field of computing, and ways that youth can disrupt learning and career contexts that do not welcome their intersecting identities of race/ethnicity, gender, etc." We argue that the same recommendation is applicable to higher education computing courses.

Our research aligns with other recent works aiming to weave DEI into the undergraduate computer science education experience. Lewis created and distributed "Microagressions: The Game!" to practice responding to microagressions [15, 30]. Many other excellent resources for promoting inclusion can be found at the csteachingtips.org website [29]. Recently, Washington advocated for creating a course specifically on gender, race, and computing [31]. We strongly support this recommendation and plan to follow up with a similar course in addition to our approach proposed here: to provide interventions in computer science *technical* classes requiring students to interact with DEI issues using the technical topics they are currently learning. We suggest that a well-crafted undergraduate curriculum would include numerous similar interventions in technical courses throughout the curriculum that directly articulate with issues covered in a course on gender, race, and computing.

3 THE INTERVENTIONS

Our two interventions were embedded within a text mining special topics course. Texting mining can be viewed as a subset of natural language processing and data mining used to extract information from text. One of the algorithms covered within the course was naive Bayes for sentiment classification [13, 22]. Using naive Bayes requires the use of a training data set to build the model. Once the model is built it can be applied to the test data and each data item can be classified into categories, often as "positive/negative".

For our primary intervention we chose to use survey data from a Partnership For Equity project engineering course intervention as the basis of our sentiment classification assignment data set [20, 24]. The survey was administered in an engineering course at West Virginia University. In that course students were asked to watch Ms. Boulamwini's 2016 TedX talk and answer a set of survey questions to help them reflect on the intersection of (in)equity and engineering. To help our computer science students fully understand the data set, we asked them to also watch the same TedX video and answer the following four survey questions drawn from the original set of survey questions:

Q1 - Ms. Buolamwini stated: "Training sets don't just materialize out of nowhere. We actually can create them. So there's an opportunity to create full-spectrum training sets that reflect a richer portrait of humanity." Do you agree with the speaker that poorly designed training sets can be a problem? Why do you agree or disagree?

Q2 - Ms. Buolamwini stated, "Georgetown Law published a report showing that one in two adults in the US – that's 117 million people – have their faces in facial recognition networks. Police departments can currently look at these networks unregulated, using algorithms that have not been audited for accuracy." Does this situation concern or reassure you? Why?

Q3 - Is this video relevant to this course? Why or why not?

Q4 - Do you agree or disagree with the following statement and why do you agree or disagree? "This video should be watched by all about to enter computer science (software development) careers."

We tasked our students with classifying survey responses for question Q1 above. We combined the answers from the engineering class survey with the answers from our class. Even so, the data set was much too small to effectively train the model. To make the model more accurate we added additional fictitious survey result data that used words such as "racism", "inequity", "justice", "bias", and "societal" and then made sure some of the test queries also included these words. These additions helped build a model that resulted in test data classification with better accuracy than would otherwise have been achieved with such small data sets. Our data set additions were explained to the students as well as the reason for them. We believe this is good pedagogy, but at the same time acknowledge this is not good machine learning practice as we are "cooking the dataset" to achieve a desired outcome. Since all of the survey answers agreed with the statement, we asked the students to classify the responses into two categories of why they agreed with the statement: "technical" or "equity". By "technical" we mean that the survey response points out technical issues such as insufficient training set size. By "equity" we mean that the survey response stated issues about how the face recognition data sets failed to consider images from a diverse population, i.e. the problem with the face recognition software training set data in the TedX talk.

The key goal of the assignment was three-fold: a) to have students hand-code and successfully use the naive Bayes algorithm; b) to scrutinize the data and understand the probabilities assigned to each word in each survey response text string so as to better understand how naive Bayes is working; and c) to encourage students to think about how DEI issues intersect with computing. Goal b reinforces goal c, thus, students truly engage with this data set bias issue which in turn allows them to think more broadly about DEI in computing.

In addition to the naive Bayes survey analysis assignment, we included a secondary more subtle intervention by using a women's clothing e-commerce review data set [14] as an ongoing sample data set. The inclusion of this quarter-long example data set sought to "normalize" consideration of a female-focused topic within a technical computer science course and is why questions EQ2 and the second part of EQ3, below, seek to address gender inclusion. In general, based on the survey answers, the women's clothing data set intervention had less of an impact on students relative to the naive Bayes assignment.

At the end of the quarter, 5 weeks after this assignment, students took another survey that asked questions about this assignment. Eleven of the fifteen students completed the final survey where students were asked four questions:

EQ1 - Think about the assignment on using naive Bayes to analyze the engineering survey data about the Buolamwini TedX talk (on face recognition failing to recognize her face). Did this assignment cause any change in your awareness or support of diversity, equity and inclusion (DEI) efforts in computing and society? If yes, how so? If not, why not?

EQ2 - Undergraduate computer science representation of those who identify as women is less than 20%. As your instructor, I have tried to be intentional about being more inclusive of people who identify as women. What assignments felt more inclusive of those who identify as women? Please explain. What assignments felt less inclusive of those who identify as women? Please explain.

EQ3 - We had two activities about inclusion in class: 1) Boulamwini talk survey data analysis; and 2) ongoing use of women's clothing data set. Did these activities impact how you think about computer science? Did these activities impact the culture of our class? If yes, how so? If not, why not?

EQ4 - Do you feel text mining can be used for social good? If so, how? If not, why not?

4 SURVEY RESULTS

The Boulamwini TedX talk [4] survey results from the engineering class are contained in another paper [24] dedicated to that intervention and not reproduced here. Given that our respondents are computer scientists, not engineers, we find it instructive and more complete to provide some reflection on our students' answers to the Boulamwini TedX talk survey. We note that students took this survey, question Q1 .. Q4, before they started the naive Bayes assignment and that their answers were included in the data set they used for the assignment. Thus, these survey results do not speak to the impact of the full intervention, only the impact of watching the TedX video.

4.1 Beginning of Project Survey

Of the 14 responses to Q1, all agreed that poorly designed training sets can be a problem, and half used the word "bias" in their answer, whereas half just used the words "poor" or "poorly designed". Some students answered with more thoughtful answers indicative of the potential negative impacts on people and society with answers such as:

- "I absolutely agree with the speaker that poorly designed training sets can be a problem, because they can perpetuate the systems of discrimination in our society. There have been literacy tests, the Grandfather Clause, gerrymandering, and voter ID laws. Society should be moving away from discriminatory practices, not inadvertently or consciously continuing them."
- "Poorly designed training sets can definitely be a huge problem. If a training set is poorly designed, then it will not properly train people and create a chain affect [sic] of problems, which can create life threatening mistakes."
- "Yes; the better you are able to represent the population your data draws from, the better prepared your program will be to accurately assess what it comes across. This makes common sense, and yet it is so easy to ignore if we are [not] thinking outside of our normal CS bubble. Many of us don't think about or want to think about social impacts our programs can make, especially at the early stages of a project."

Of the 14 responses to Q2, 86% expressed concern citing issues of mistaken identity, privacy violations, or general worry about a police state. One response indicated ambivalence, and another being resigned to the practice and a sense of powerlessness to make change.

Of the 14 responses to Q3, 79% stated they agreed the video was relevant to the course. Many answers stated it was relevant because of the importance of training set selection in machine learning algorithms.

Of the 14 responses to Q4, 79% stated they agreed all computer science students should watch this video, most citing students need to be aware of how bias can negatively impact computer science products. The 21% who disagreed all stated that it was applicable to machine learning but that not all computer science students will take or work with machine learning.

4.2 End of Quarter Survey

The end of quarter survey, questions EQ1, EQ2, EQ3, and EQ4 above, speak directly to the impact of the intervention. Eleven of the fifteen students completed this survey.

Of the 11 responses to EQ1, 55% of students indicate the assignment increased their awareness and support of DEI efforts in computing and society, 27% indicated they were already keenly aware of these issues and hence this assignment simply reinforced their support; and the remaining 18% made no mention of DEI concepts and instead only wrote about how the assignment made them aware of the importance of training set size.

Almost all answers to EQ2 stated they thought the assignments were in general inclusive and the answers tended to be short. One answer stood out as especially interesting:

- "I have really never been asked this before. Nothing felt exclusionary or specifically oppressive, e.g. if the clothing data set had been replaced by men's underwear reviews or something. I honestly don't know what an inclusive curriculum would feel like except by the absence of exclusion. It was a little uncanny at times to be working on CS, which I associate strongly with masculinity, and reading reviews about a stereotypically feminine topic. I liked the discord."

Of the 11 responses to EQ3, 64% stated it impacted how they think about computer science and 36% stated it did not. Only 27% of the 11 stated the women's clothing data set impacted how they thought about computer science, 18% stated it did not, and 55% made no mention of it one way or the other. Example responses that speak to impacting how students think of computer science include:

- "I think both activities brought greater and continued awareness about the value and impact of data, and how even something that's "all math" and "all logic" can involve social and even ethical aspects."
- "The Boulamwini talk survey data analysis impacted how I think about computer science. Even a subject matter that seems to be unable to express any human traits, because humans created these programs, there will be evidence of some sort of bias in them. Now I am questioning if even math have any evidence to show human bias or not. The answer to this question depends on whether math is a concept that is discovered or created. "
- "These did impact how I felt about computer science, as I was unaware of how bias can be created in software, and how analyzing a data set about things you are not knowledgeable about can be more difficult."

All 11 responses to EQ4 stated they felt text mining could be used for social good. Several responses gave concrete examples:

- "For example, you could analyze the tweets of groups to determine whether they are true to their name or are fake accounts run by opposing groups."
- "My immediate thought is using text mining in order to help protest organizers to keep up to date on what is happening across a protest through twitter. Being able to crawl Twitter and give appropriate information to protest organizers will allow them to understand how their protest is going, where bad operators may be, and where people may be in need of assistance."
- "I think that text mining can be used to find hate accounts or spam accounts that distract from social change on social media, so that they can be taken down. However, this tool must be used carefully, because it may cause excessive censorship by taking down accounts that have a lot of the same trigger words as the hate accounts, but instead only have those words to explain their meaning and keep people informed."
- "I definitely think it could help for the social good- in this day and age- keyboard warriors are prevalent and especially with how important mental health has become in our era, I believe that text mining can help in the minimization of stopping cyber bullying."

While it would be hard to conclusively claim that our interventions directly seeded this line of thinking, we are encouraged to see such thoughtful responses.

5 CONCLUSION

Although we cannot claim statistical significance due to small sample sizes, we argue there are practical implications and "human significance" from this project which can support computer science educators in intentionally designing assignments that help computer science students develop inclusive computing mindsets. First, over 50% of the students articulated that this assignment increased their awareness of how an allegedly objective field like computer science can actually be subjective because "humans created these programs" while 100% of students saw the benefits of harnessing text mining as a way to contribute to the social good. The qualitative composite of the students' open-ended responses suggest depth and breadth to their understanding of the relationship between DEI and computer science. Second, we posit that assignments like these also help to create an inclusive climate, thus further supporting women and racially minoritized students. According to DEI scholars [8, 12, 26], when students can create relevance and connections between academic content and their personal lives, they are more likely to engage deeply with school and persist in their pursuit of higher education. Third, this course and intervention occurred during a time of national health and social crisis which undoubtedly had an impact on the experience. The course was online, due to the corona virus pandemic, and ran from March 30 through June 6 2020, concluding after the murder of George Floyd, thus elevating student awareness of equity issues at the time of the final survey. By creating an equity-minded assignment that highlighted both technical expertise and social concerns, the activity provided space for students to intentionally cultivate relationships between their personal lives and the classroom, a pedagogical move which reminds us of the importance of tending to the whole being of our students and ourselves as teachers.

6 ACKNOWLEDGMENTS

This work has been supported in part by National Science Foundation grant DUE IUSE-EHR #1726268. We would like to thank Professor Karen Rambo-Hernandez for providing the engineering survey data set and survey questions that served as a seed for this intervention, several discussions about using machine learning for qualitative assessment analysis, and for critiquing our final survey questions.

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