Link to Rachel R's and Emily's original facilitation guide to pull

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Setting Norms

This assignment relies heavily on discussion, as well as interrogating potentially sensitive topics on bias, discrimination, and systemic inequality. Students have or will have to deal with bias and discrimination in their lives, unfortunately. *Norms are vitally important to make sure everyone is on the same page about how we conduct ourselves*. Creating norms not only signal the importance of treating each other with respect but can serve as a way to intervene if students are not following them. Below are some examples of norms that are we like to use:

- Make space, take space: share the air
- Listen to understand, not to judge
- Speak for yourself, not for others
  - avoid generalizations
  - respect others' experiences
- Consider whose viewpoints are not included in our conversations
- Use both/and rather than either/or thinking
  - "Yes, and" language
- Be aware of, and work to deconstruct, the existing power dynamics in the room
- Impact is not the same as intent (i.e. you may not be trying to cause harm (intent), but you can still be causing harm (impact))

This is not an inclusive list. If you have already developed class norms, remind your students of them. If you have not, this is a place to start.

Things Students Might Bring Up (and How to Respond)

- "What if one group (orange here) of individuals was really smarter than the other?"
  - If you are saying one group of individuals is smarter than the other, how are we defining "smarter". If they have more of things like internships, classes, resumes,

opportunities, think about how this relates to who gets these opportunities based on societal bias

    - We know that aspects like intelligence are not fixed traits or things you are born with. The 'resumes' being shown in the game capture things that aren't necessarily innate (like people often perceive intelligence), such as "work experience" and "school prestige" which are based on access and opportunity.
        - Example - Olympians often have olympian parents. This is more due to the intersection of access, opportunity, and wealth than genetics.
  - This is a generalization. No one group is homogenous in the same group. Not all of one group is smarter than all of another.
  - Historical approach to intelligence: https://www.facinghistory.org/resource-library/racism-intelligence-test-scores

- "What if you just change the algorithm? What if we just made the algorithm unbiased?" ○ Bias is rooted in all aspects of the hiring process, since bias is systematically inherent in our society. You can't untangle the bias from the algorithm. ■ You can take steps to mitigate the bias, but you cannot remove it entirely. ○ Examples to mitigate bias:
    - In the hiring process, having training for implicit bias for folks are on the hiring committee.
    - Normalizing for opportunities (i.e. of the opportunities a candidate had available to them, what did they do?)
  - From a software perspective: It is not as simple as hitting a button or flipping a switch to remove the bias. It is a complex, multi-faceted problem.
- "The algorithm is rigged"
  - Students might recognize the deterministic aspect of the algorithm and question why it was created that way. Remember that this was created as an educational tool. You should challenge students to think about why this tool was created and what choices were made?
  - This came up in previous semesters, and we have made updates to the PCA/ICA to address this. See section PCA Section: "What's actually happening in the simulation?"
- "Good thing I was born in a good zip code" The impact of zip codes and location they grew up in.
  - Students might notice the city parameter is skewed to 0 for the blue people and 1 for the orange people. These are related to access and opportunity and ties to points made in other bullets. It is a structural problem, not something easily fixable.
  - There is a lot to unpack and point to here: redlining, structural racism, property taxes, public school education, generational wealth
    - Lansing as an example:
        - https://storymaps.arcgis.com/stories/19e90e698bc44081b7eb6dbea3506c3d
        - https://www.lansingography.com/2022/10/the-racial-makeup-of

        - -lansing-2016-2020.html
        - https://www.reddit.com/r/lansing/comments/y93kmn/lansing_by_race_neighborhoods_from_20162020/?utm_source=share&utm_medium=web3x&utm_name=web3xcss&utm_term=1&utm_content=share_button
    -
        - Redlining: https://www.npr.org/2017/05/03/526655831/a-forgotten-history-of-how-the-u-s-government-segregated-america
        - Racial and Generational Wealth: https://www.aclu.org/news/racial-justice/visualizing-the-racial-wealth-gap
        - School choice: https://time.com/6322715/school-choice-black-children-essay/
- De-escalation with potential racist and sexist students
    - First priority, minimize harm to other students.
        - This means making sure that you don't ignore the behavior (that tacitly approves it)
        - Depending on the entry point for the student and what they are expressing opinions on, you can use the talking points from above.
        - If the student continues to argue or escalate, call them back into the norms for the day and the norms for classroom behavior (e.g. "I'm hearing that you have some strong opinions, but I want to remind you that this is an inclusive classroom space and what you are sharing may come across to others as harmful. I/we expect you to engage respectfully with your colleagues and instructors.")
            - If you are a TA or ULA, feel free to tag in your section lead for this type of interaction
            - If you are faculty and the student is not responding well, ask them to step outside for a moment
            - If needed, you can cite our syllabus policy and ask the student to leave class for the day (and penalize their grade accordingly)

Pedagogical Backing: Why Should We Care?

Summary:

- Why this assignment is important
    - Algorithms are quickly becoming embedded in various aspects of our lives. Students need to be made aware of how bias is integrated and can affect real-life situations.
    - Students should be equipped with Data Literacy skills

        - "Data literacy is the ability to ask and answer real-world questions from large and small data sets through an inquiry process, with consideration of ethical use of data" (Wolff, et.al, 2016)
    - The assignment challenges students to think about how bias is embedded into data collection, the existence of this bias in the model it is used in, and the implications of using the results from these models.
- The assignment fits with learning objectives for the course
    - Algorithmic Bias; Recognize and Articulate Context of Data
    - Reading, Writing, and Using Authentic Code

Algorithms can wreak profound damage on lives by making decisions on everything from where we go to college and get a job, to obtaining insurance (O'Neil, 2018). In 2020, Detroit Police arrested perhaps the first person wrongfully arrested due to a false match of a facial recognition algorithm. Mr. Williams, the victim of this algorithm, was a black man (Hill, 2020). It is known that while the software might work well on white males, it is much less accurate for other demographics. This point is emphasized by Joy Buolamwini, a Black researcher who found standard facial recognition software wouldn't recognize her face unless she donned a white mask (7th Empire Media, 2020). The nuance of data is also incredibly important; data should not exclude whole populations, but we must also be careful that including them will not also perpetuate harm. Issues of privacy, power, and visualization within data are all important for data scientists to grapple with (D'Ignazio & Klein, 2020).

While this seems to have been recognized across the field, guidance on implementing data ethics and algorithmic bias into the curriculum is not always clear. For example, the Curriculum Guidelines for Undergraduate Programs in Data Science published in 2017 identifies six key competencies for an undergraduate data science major: computational and statistical thinking, mathematical foundations, model building and assessment, algorithms and software foundation, data curation, and knowledge transference - communication and responsibility (De Veaux, et. al.). The guidelines specifically mention the importance of ethics within the category of knowledge transference- communication and responsibility. Even so, in the proposed curricula and potential class descriptions, ethics do not show up anywhere. Instead, it is labeled as a 'related course,' and not included in the list of "the bare necessities of the material required for a data science major" (De Veaux, et. al.).

Without data ethics, care, and social responsibility in the curriculum, or not being addressed in broader ways, narrow-minded, problematic ideas may be perpetuated. Gunckel and Tolbert examine engineering education (especially within the *Framework* and NGSS) with critiques of neoliberalism, utilitarianism, and technocracy. While noting that postsecondary engineering education has begun to address ethics and social responsibility, the authors highlight problematic factors such as focus on micro-ethics between client and engineer and assumptions of rational actors who may follow logical steps to solve the ethical dilemma (2018). Their reflections directly relate to data collected on undergraduates. In a survey asking over 5,500 students of various majors before and after their college careers, participants selected their level of agreement to four statements: *i) I am actively working to foster justice in the world, ii) I frequently think about the global problems of our time and how I will contribute to resolving them, iii) I am currently taking steps to improve the lives of people around the world, and iv) I am actively learning about people across the globe who have different religious and cultural ways of life than I do*. Not only did engineering and computer science majors have lower agreement scores overall compared to other majors, but their agreement with these statements *decreased after* their years of college study. It is unclear how many of these students, if any, were exposed to ethics and 'global citizenship' in their classrooms (Núñez, et. al., 2021).

Pedagogical Backing: Data Literacy

While the definition of data literacy is actively still being developed (Gummer, 2015; Wolff, et.al, 2016; Schield, 2005; Dichev, 2017), Wolff, et. al. (2016) has converged on the following definition through conducting a literature review of relevant papers in the field:

> *"Data literacy is the ability to ask and answer real-world questions from large and small data sets through an inquiry process, with consideration of* ***ethical use of data****. It is based on core practical and creative skills, with the ability to extend knowledge of specialist data handling skills according to goals. These include the abilities to* ***select****, clean, analyze, visualize,* ***critique and interpret data, as well as to communicate stories from data and to use data as part of a design process."***

The aspects of the definition we highlighted in our task are indicated in bold above.

Wolff, et. al. (2016) emphasizes the importance of ethics and understanding the role and impact of data in different contexts as competencies that should be present in all aspects of the data inquiry cycle. Additionally, Utts (2003) identified understanding "Biases in Surveys" as one of their seven topics that educated citizens should know about statistics and probability. As presented by Utts, this included phrasing of survey questions, ordering of survey questions, and development of these questions for varying audiences. As surveys are a common form of data collection, the concerns presented extend to our considerations. Both of these authors highlight both the high level of bias we face in data, as well as the inevitability of interacting with this data on a daily basis.

It is important to note that across the literature there is not a cohesive and comprehensive definition of data science literacy. Most include some aspect of collecting, analyzing, visualizing, and interpreting data, but make no claims as to the
necessary level of these skills and how they are defined on a fine-grain level. Additionally, courses covering data science and literacy describe the key components they feel are necessary to the course which align with the stated aspects, but few deeply describe the implementation of these skills (Dichev, 2017; Schreiter, et.al, 2024). Since it is unclear at what skill level one becomes 'literate,' we created multiple access points to the material that can be expanded and adapted for various levels.

Related to the presented definitions, our task focuses on giving students exposure to the ethics in data. This includes how bias is embedded into data collection, the existence of this bias in the model is used in, and the implications of using the results from these models. Students think critically about the choices the creators made to create the simulation and how this represents real-world stereotypes and bias.

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