***All our work including the below information and the Jupyter Notebook can be viewed in this repository. This task was developed by Rachel Roca and Emily Bolger.*

Overview Table:

Below is an overview of the assignment. Underneath this section, there will be more comprehensive information, as well as within the instructor notebooks. This table does not include the variations of the assignment explained within the website.

Task	Timing	Participant Structure	Notes
Pre-Class: Play the Game	Minimum: 10min Recommended: 15min	Individual asynchronous work	Facilitators should also play the game several times to familiarize themselves with the material
Pre-Class: Reflections	Minimum: 10min Recommended: 15-20 min	Individual asynchronous work	Facilitators should reflect on the questions as well, and also consider the material in the instructor guide.
In-Class: Opening	Minimum: 10min Recommended: 15-20 min	Lecture Style	Facilitators should introduce the material for the day, have a discussion on norms, and complete any "housekeeping." See template slides for scaffolding.

In-Class: Initial Discussion In-Class: Looking at the code *For the advanced ICA, plan to block out closer to an hour for this section.* In-Class: Article	Minimum: 15min Recommended: 20-30 min Minimum: 20min Recommended: 30-40 min Minimum: 10min Recommended: 15-20 min	Small groups and full class discussion Small groups Individual reading, small group discussion	Facilitators should float around the room, listening and engaging with students, before bringing everyone in for a full class discussion. Facilitators should float around the room, listening and engaging with students, and answer any questions. Facilitators should prepare to make sure they are familiar with what is going on in the code. Facilitators should float around the room, listening and engaging with students, and answer any questions. Facilitators may consult with the instructor guide material for additional insight.

In-Class: Wrap up Discussion	Minimum: 10min Recommended: 15-20 min	Full class discussion	Facilitators should lead and moderate this discussion. See instructor guide material for additional insight on facilitation.

Task:

Below is the general framework of the assignment, which is divided into three parts. The first part takes place in the pre-class assignment, and the last two parts take place in the in-class assignment. Between each part, there will be time for discussion and reflection. Specifics can be found in the instructor's version of the pre and in class assignments.

Play the Game - Pre Class

Learning Objective: Step into the role of using AI to solve a task, and identify the potential consequences when utilizing these tools.

TO DO:

1. Play through "Survival of the Best Fit" while considering the following questions:

- Reflect on intention vs. impact. Why was an algorithm used in the first place? Was the intention malicious? What was the impact on the candidates?
- What was your strategy when choosing who to hire? How did the game react to your choices?

i. **Facilitator's Note: mention what is built in deterministically- how does this extend to limitations of simulations/models in general? This can be discussed during the beginning of the in class assignment.**

c. Were you surprised when you reached the end of the simulation? Why or why not?

2. If you have time/want to, play through the simulation a few times. What aspects stay the same? What changes? Regardless of the choices that you make. **Facilitators should play the game several times to be familiar with simulation as well.**

Look at How the Data was Constructed - In Class

Learning Objective: Dive deep into the data creation process and the model building for "Survival of the Best Fit," including the choices that were made to implement bias.

TO DO:

1. Read through the pieces of the Jupyter Notebook ('biased_data_gen' file) used to create the data and the model for "Survival of the Best Fit" on (based on the creator's GitHib repository).
2. Discuss/think about the questions posed in the notebook regarding data creation.
3. What remaining questions do you have? Pose it to your group or class.

Facilitator's Note: Make sure you're familiar with the code, students may ask you questions about lines they don't understand. Be sure to celebrate how much they know! Most students have very little coding experience when they come into an introductory data science course. They can now read several chunks of code written by professionals that weren't designed for students. This is a time to celebrate how far they've come and build up their confidence and self-efficacy. Facilitators should be interacting with students during this time, circling the classroom, and answering questions.

For the advanced version of this assignment, students will need more time to construct their own data and associated models. Facilitation follows closely to the base assignment: facilitators should be circulating the class answering questions and prompting more discussion. Special attention can be paid to the assumptions students make when simulating data and

designing a model. This is also a great point to celebrate students' ability to write code on the spot, as well as comprehend code.

Real Life Application and Discussion - In Class

Learning Objective: Understand bias in data and algorithms in the real world, outside of toy simulations.

TO DO:
1. Read the article "Amazon ditched AI recruiting tool that favored men for technical jobs".

2. Consider the following questions:

- What connections do you see between "Survival of Best Fit" and Amazon's real-life recruiting tool?
- Why was the algorithm biased in this case? What was biased about the training data?
    i. How did "Survival of the Best Fit" integrate this type of bias when creating their data? How did it affect the performance and results of their model? ii. How does the simulated data and the real data represent systemic issues present in our world?
- What components of bias did you notice when playing the game, if any? ● How would you feel if you knew the company you applied to was using AI to judge candidates? Why or why not? Related, if you were in a hiring role, would you feel comfortable using AI to aid in hiring decisions? Why or why not?

Facilitator's Note: Consider the norms below when having this conversation with your students. If you don't already have norms for your classroom, this assignment is a great time to set them. Students each have different experiences in their lives up to this point and it is important to make sure these conversations do not lead to harmful experiences for the students.

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

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.

Pedagogical Backing: Why Should We Care?

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.

References

7th Empire Media. (2020). *Coded Bias*. Retrieved from https://www.codedbias.com/.

Bahl, U., Topaz, C. M., Obermüller, L., Goldstein, S., & Sneirson, M. (2023, May 1). Algorithms in Judges' Hands: Incarceration and Inequity in Broward County, Florida. https://doi.org/10.31235/osf.io/326tw

De Veaux, Richard D., Mahesh Agarwal, Maia Averett, Benjamin S. Baumer, Andrew Bray, Thomas C. Bressoud, Lance Bryant, et al. (2017, March 7). Curriculum Guidelines for Undergraduate Programs in Data Science. *Annual Review of Statistics and Its Application* 4. https://doi.org/10.1146/annurev-statistics-060116-053930.

Dichev, C., & Dicheva, D. (2017). Towards Data Science Literacy. *Procedia Computer Science*, *108*, 2151–2160. doi:10.1016/j.procs.2017.05.240

D'Ignazio, C., & Klein, L. F. (2020). *Data feminism*. The MIT Press.

Gummer, E. S., & Mandinach, E. B. (2015). Building a Conceptual Framework for Data

Literacy. Teachers College Record, 117(4), 1-22.
https://doi.org/10.1177/016146811511700401

Gunckel, K. L., & Tolbert, S. (2018). The imperative to move toward a dimension of care in engineering education. *Special Issue:A Critical Examination of the Next Generation Science Standards*, *55*(7). Retrieved December 14, 2022.

Hill, K. (2020, June 24). *Wrongfully accused by an algorithm*. The New York Times. Retrieved December 14, 2022, from
https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html

Núñez, A.-M., Mayhew, M. J., Shaheen, M., & Dahl, L. S. (2021, March 15). *Let's teach computer science majors to be good citizens. the whole world depends on it. - edsurge news*. EdSurge. Retrieved December 14, 2022, from
https://www.edsurge.com/news/2021-03-15-let-s-teach-computer-science-majors-to-be-good-citizens-the-whole-world-depends-on-it

O'Neil, C. (2018). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Penguin Books.

Shields, M. (2005). Information Literacy, Statistical Literacy, Data Literacy. *IASSIST Quarterly*, *28*(2-3), 6. https://doi.org/10.29173/iq790

Stemwedel, J. D. (2014, May 28). *Resistance to ethics is different from resistance to other required courses*. Scientific American Blog Network. Retrieved December 14, 2022, from
https://blogs.scientificamerican.com/doing-good-science/resistance-to-ethics-is-different-from-resistance-to-other-required-courses/

Utts, J. (2003). What Educated Citizens Should Know About Statistics and Probability. *The American Statistician*, *57*(2), 74–79. https://doi.org/10.1198/0003130031630

Walczak, Kelley, Cynthia Finelli, Matthew Holsapple, Janel Sutkus, Trevor Harding, and D. Carpenter. (2011, April 27). Institutional Obstacles to Integrating Ethics into the Curriculum and Strategies for Overcoming Them. In *Integrating Engineering Ethics into the Curriculum (*American Society for Engineering Education).

Wolff, A., Gooch, D., Cavero Montaner, J.J, Rashid, U., Kortuem, G., (2016). Creating an understanding of data literacy for a data-driven society. The Journal of Community Informatics, 12(3), 9-26