# Module 1: Introduction: What Is Human-Centered Data Science?

Instructor Guide

Module Objective

Upon completion of this module, students will be able to:

* Define Human-Centered Data Science
* Explain what does “human-centered” adds to data science
* Introduce methods of Human-Centered Data Science

This guide serves to assist instructors with applying Module 1 to their own course settings. We have provided the following materials for this module: slide deck, group activities, individual activity, recommended complementary readings, and a code notebook example. All materials are ready to be applied directly in course settings (shared through a Learning Management System); however, we provide details in this guide as to how to adapt the materials to fit your course setting.

Slide Deck

| Slide Number(s) | Content | Timing/Notes (Total: ~ 3 hours in-class content) |
| --- | --- | --- |
| 1-2 | Introduction | 2 min: Adapt to class needs/learning objectives. |
| 3-7 | Algorithmic Bias | 20 min: Providing an understanding of “human-centered” concerns and bias. Recommend instructors to provide examples and engage students in discussion. |
| 8 | Activity 1 | 20 min: Peer-peer activity to discuss social media behaviour. Optional: have student pairs report their answer back to the class. |
| 9-13 | Human-Centered Data Science | 20 min: Providing an understanding of why human-centered methods are important. |
| 14 | Activity 2 | 20 min: Peer-peer activity to discuss privacy & AI tools. Optional: have student pairs report their answer back to the class. |
| 15-20 | Methods | 15 min: Providing an understanding of how to approach/apply human-centered data science. These five principles (slides 16-20) are carried through future modules. |
| 21 | Activity 3/Group Exit Ticket | 20+ min: Group activity for students to reflect on who the “humans” are in the data science pipeline. Recommend that students submit a slide or written/drawn deliverable for instructors to assemble and provide back to students after each lecture. |
| 22 | References | Literature cited/referenced in this slide deck. |
| Code | Module 1 Notebook | Up to 60 min: Break + Code notebook example (logistic regression) and discussion. |

Slide Deck Variations

* To shorten the lecture: decrease the amount of time spent on each slide and/or shorten the activities. Activities 1 and 2 can instead be completed by the class as a whole in a group discussion setting.
* To lengthen the lecture: add examples of commonly known algorithms (social media, health risk predictions, LLMs) to the slides and engage students in discussion. Increase the complexity of the activities and/or ask students to submit their answers for evaluation.
* 50-min version: Slides 1–7 + Activity 1 + Slides 9–13 + short debrief.
* 80-min version: Full slide deck (minus code notebook and activities 1 & 2).

Exit Tickets

“Exit tickets” are optional assignments that students can complete at the end of a course session, to cement their understanding of that lecture’s key takeaways and engage in thought-provoking activities before heading out the door.

Group Exit Ticket

The group exit ticket for this module engages students in small groups (2-5 people, depending on class size) to explore the role of humans in data science. A description of the activity is provided on Slide 21 of the provided deck.

We recommend that student groups submit their created slides/deliverables (whether or not they are graded/recorded for participation), so that instructors can assemble all slides/deliverables and give them back to students as a way to revise from the work their peers have completed. Instructors can collect group exit tickets from throughout the semester to assemble a student-generated understanding of human-centered data science.

Individual Exit Ticket

We provide an individual exit ticket should instructors like to assess students individually and/or perform a knowledge check from the textbook/readings.

1. What is not an assumption of human-centered data science?
   1. **Algorithms are not by their nature biased**
   2. Data sets contain bias because of who is represented and who is not
   3. It is important to select the right data set for a data question not the easiest to find
   4. Data science questions should be crafted around the why
2. Which of the following is a human-centered data science method/approach?
   1. Data visualization
   2. Machine learning
   3. **Contextual understanding**
   4. Data collection and labelling
3. Which of the following are people in the data pipeline?
   1. End users/subjects
   2. Populations represented in the data
   3. Data scientists
   4. **All of the above**
4. Which is not an example of possible bias in data science?
   1. Historical data missing certain populations
   2. Algorithms built to mimic current processes
   3. Expectations of data scientists of the correct outcomes
   4. **Statistical error**
5. Which is the definition of the “Portability Trap” as presented by Selbst et al.?
   1. Failure to understand how the insertion of technology into an existing social system changes the behaviors and embedded values of the pre-existing system
   2. Failure to account for the full meaning of social concepts such as fairness, which can be procedural, contextual, and contestable, and cannot be resolved through mathematical formalisms
   3. **Failure to understand how repurposing algorithmic solutions designed for one social context may be misleading, inaccurate, or otherwise do harm when applied to a different context**
   4. Failure to model the entire system over which a social criterion, such as fairness, will be enforced

Readings

We recommend the following readings to complement this module:

1. C. Aragon, S. Guha, M. Kogan, M. Muller, and G. Neff. 2022. Human-Centered Data Science: An Introduction. MIT Press. ISBN: 9780262543217 **Chapter 1: Data Science to Human-Centered Data Science.**
2. C. D’Ignazio and L. F. Klein. 2020. *Data Feminism*. MIT Press, Cambridge, MA. DOI: 10.7551/mitpress/11805.001.0001
3. V. Eubanks. 2018. *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. St. Martin’s Press, New York, NY.
4. M. A. Madaio, L. Stark, J. Wortman Vaughan, and H. Wallach. 2020. Co-designing checklists to understand organizational challenges and opportunities around fairness in AI. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI ’20)*. ACM, New York, NY, 1–14. DOI: 10.1145/3313831.3376445
5. C. O’Neil. 2016. *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. Crown, New York, NY.
6. D. Saxena, K. Badillo-Urquiola, P. J. Wisniewski, and S. Guha. 2021. A framework of high-stakes algorithmic decision-making for the public sector developed through a case study of child-welfare. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2, Article 348, 1–41. DOI: 10.1145/3476089
7. D. Saxena, E. Seh-Young Moon, A. Chaurasia, Y. Guan, and S. Guha. 2023. Rethinking “risk” in algorithmic systems through a computational narrative analysis of casenotes in child-welfare. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI ’23)*. ACM, New York, NY, 1–19. DOI: 10.1145/3544548.3581308
8. A. D. Selbst, D. Boyd, S. A. Friedler, S. Venkatasubramanian, and J. Vertesi. 2019. Fairness and abstraction in sociotechnical systems. In *Proceedings of the 2019 Conference on Fairness, Accountability, and Transparency (FAT\* ’19)*. ACM, New York, NY, 59–68. DOI: 10.1145/3287560.3287598

Instructors are encouraged to add, replace, remove readings as they see fit.

Code Notebook

The provided code notebook (tested in Google Colab/Jupyter and requiring skikit-learn, pandas, matplotlib) presents an example of training a logistic regression model on a biased dataset. We provide the code to create 1) a synthetic data set, 2) visualizations examining the data, 3) a logistic regression model, 4) post-hoc analysis.

The purpose of the code notebook is to provide students with a hands-on example of a human-centered data science problem and potential biases. This activity is best suited for students with basic Python and introductory machine learning knowledge.

The code can be adapted as instructors see fit, including lengthening the example, creating more/different features, increasing the complexity of the model, and/or using your own dataset. Instructors with non-technical cohorts can use the virtualizations only and skip the modeling code.