SIADS 503: Data Science Ethics

School of Information, University of Michigan, March 2024
This document includes:
I. Course Basics
II. Course Schedule (list of required readings for each week)
III. Further Readings/Listings (related to each week's topics)
IV. Additional Course Policies
V. Acknowledgements

I. Course Basics

Course Overview and Prerequisites

This class will teach you to recognize where ethical issues can arise when applying data science to real world problems. It will bring more analytic precision to ethical debates about the role that data science, machine learning, and artificial intelligence play in consequential decision-making in commerce, employment, finance, healthcare, education, policing, and other areas. Largely through discussions of case studies, we will focus on ways to conceptualize, measure, and mitigate harm in data-driven decision-making. You will learn to think critically about how to plan and evaluate a data science project with ethical concerns in mind, and how to cope with novel challenges for which there are often no easy answers or established solutions. To do so, you will learn key technical, ethical, policy, and legal terms and concepts that are relevant to ethical assessment in data science; learn about some of the common approaches and emerging tools for mitigating or managing these ethical concerns; and gain exposure to readings that will help you understand the current ethical and regulatory environment and to anticipate future developments. Ultimately, the class will teach you how to reason through these problems in a systematic manner and how to justify and defend your approach to dealing with them.

The prerequisites for this course are admission into the Masters in Applied Data Science program and successful completion of SIADS 501, "Being a Data Scientist."

Instructional Team

Instructor: Merve Hickok
Instructional Team: Dr. Nick Sheltrown; Ruth Corddry; Alexis Castellanos
                                 Sachit Krishnan; Emily Schemanske; Bulgan Jugderkhuu
Members of the instructional team play different roles:
- Melissa and Merve have recorded course videos and iterated course content (e.g. readings, assignments, and quizzes) since the course was launched in 2020. They, along with Nick and Ruth, look forward to interacting with you about course concepts and other content on Slack and during office hours.

- Merve, Nick, and Ruth should be your first points of contact for everything related to **assignments and grading**. They are here to support your learning and will be happy to help you get the support you need to be successful in the course. (Please see "how to get help" below)
- The other lecturers supporting SIADS 503 - Alexis, Emily, Sachit, Bulgan and Mike - will spend most of their time behind the scenes grading your work, but you may also engage with them in Office Hours, or on Slack.

Communications Expectations

Slack is the primary communication mechanism between the instructional team and students for this course. If you do not use Slack, you will likely miss out on important updates, feedback, and discussions on topics of interest to the course.
- Course channel in Slack = siads503_wi24_003
- Slack response time: within 24 hours; weekend responses may be longer
- Email response time: N/A; please use Slack
- **Office Hours: Thursday, 8- 9 AM (Eastern (Ann Arbor) time), and Monday, 3 - 4 pm (Eastern (Ann Arbor) time). Please refer to the Live Events page on Coursera.**

How to Get Help

This is a large class, but it's still easy to get help if you need it:
- *Questions likely to be of general interest to other students in the class:* please post to the course Slack channel. Note that there will be pinned posts for conversations about each of the four weekly assignments.
- *To request additional individualized feedback or support on weekly assignments:* If you got feedback that you are having trouble understanding, or perhaps you disagree with it and would like some substantive advice on how to improve in future weeks, please follow these steps:
    - Write up as specific a question as you can, including enough context for the instructor team to understand it. Be sure to include your best interpretation of what the feedback is telling you.
    - Send a Slack group DM to **ALL of the following lecturers**: @Merve Hickok, @Ruth Coddry, and @Nick Sheltrown One of us will get back to you in the shared slack thread, usually within 24 hours.
- *If you have questions concerning the degree program or encounter issues using Slack*, please email umsimadshelp@umich.edu
- If you have an issue specific to the Coursera environment, you can begin a live chat session with Coursera Technical Support (24/7) or view Coursera troubleshooting guides. (You may be asked to log in to your Coursera account).

Required Textbook

You will be given a list of required and recommended readings within the course and also below in Course Schedule (Section II) and Further Readings (Section III). Online access to these readings is provided through the University of Michigan Library or through approved online sources. For resources provided through the library, you will be asked to sign in with your UMich uniqname and password to access these materials. This course does not require the purchase of a textbook.

Course Learning Outcomes

1. Understand the most critical concepts and principles of ethics that apply to data science and outcomes.
2. Identify potential harms of data collection, aggregation, analysis, and use typically found in applied data science contexts.
3. Identify potential causes of bias and discrimination using data, and evaluate whether a data-driven system is discriminatory to any system stakeholders.
4. Remain vigilant of potential discriminatory outcomes when building data science solution(s); engage in multidisciplinary conversations to actively work against discrimination for solution(s) stakeholders.
5. Understand, identify, and discuss how data and algorithms have been used to perpetuate racism; introduce how to correct, combat, and prevent racism using anti-racist data and algorithmic practices.
6. Apply course concepts to written ethical assessments and recommendations (e.g. a memorandum) for applied data science use cases (e.g. automated decision-making systems).
7. Articulate reasoning behind the most important ethical challenges of data science as applied to course domains of privacy, bias/classification, provenance/aggregation, power imbalances, accountability/consequences.

Please note that you will also see "Learning Objectives" listed at the start of each week. Think of these as "Goals for This Week."

Course Structure

Each week, this course consists of **recorded lectures, required and recommended readings**, and two **office hours** produced by the teaching team. Lectures consist of overview material about concepts as well as the discussion of case studies. In addition, a guest speaker will visit or we will take a field trip. This provides one or more additional recorded lectures, interviews, or conversations. Lectures supplement but do not always review or duplicate the readings; readings supplement but do not always duplicate the lectures. That means some of the course content is available only from a lecture or a reading. For instance a concept may not be mentioned in a lecture, but it may be the key point of a reading. Students are still responsible for that material.

A low-stakes, open-book weekly **quiz** provides an incentive to keep up with the readings/lecture content. Although Coursera shows a time in the quiz page, this is an automated estimation.

Note that there is not a time limit for the quiz, but you have only one attempt each quiz. You may begin the quiz then leave and finish later.

The primary work of the course is one **writing assignment** each week. Thorough instructions are included in the Assignments and Assessments section of each week's content. A homework guide for each assignment (linked in the instructions) can help you get started and organize your thoughts.

Office hours offer us the opportunity for the teaching team and students to discuss course topics more informally; there will be opportunities for both student-generated questions and conversation as well as teaching-team led presentations of content related to both course topics and assignments. We also hope to welcome some guests to shed light on how ethics issues manifest in real-life professional situations.

Specific information for each week is below in Course Schedule (section II).

Course Deadlines

This course begins on **Tuesday, March 5** and ends on **Monday, April 1**.
Weekly Quizzes and Writing Assignments will be due on Mondays at 11:59 pm (time zone is Ann Arbor, Michigan; Eastern Time).
The Extra Credit assignment will be due on Monday, April 1 at 11:59 pm (time zone is Ann Arbor, Michigan; Eastern Time).

Grading

Assignment type - % of Final Grade
Weekly Quizzes (4 quizzes; lowest score dropped) - 10%
Weekly Writing Assignments - 90%
- Week 1: Memo about a privacy concern (15%)
- Week 2: Evaluation of the What-If Tool (25%)
- Week 3: Perform an algorithmic impact assessment (25%)
- Week 4: Design an ethics oath, pledge, or checklist (25%)

Extra Credit – Write Your Own Quiz Questions - (up to 2.5% EC)
Note: You are required to attempt/complete **all assignments (except extra credit)** in order to earn credit for this course.

Letter Grades, Course Grades, and Late Submission Policy

Refer to the MADS Assignment Submission and Grading Policies section of the UMSI Student Handbook (access to Student Orientation course required)
Final letter grades for the course will be calculated using the following scale: A+ 98%+; A 93-97%; A- 90-92%; B+ 87-89%; B 83-86%; B- 80-82%; C+ 77-79%; C 73-76%; C- 70-72%; D+ 67-69%; D 63-66%; D- 60-62%; E 59% or below. **Coursera does not round up or down (e.g. 86.78% = B).**

Late submissions receive 10% penalty per day.

Regrade Requests Policy

Graders may make mistakes. Gradescope has a system for regrade requests; please use it to request review of an assignment, and describe why you think that the initial grading was incorrect. Regrade requests will be handled by a different grader. The entire assignment will be regraded, applying all elements of the grading rubric. Your grade could go up or down.

Revise and Resubmit

You will have the opportunity to revise and resubmit **one** assignment. This is not required, but is rather an opportunity to recover from a misstep and earn additional points by responding to feedback and improving your submission. Your revised assignment may earn up to the median score for that assignment. The assignment will be graded using the same rubric as the initial submission. We do not begin with the median grade and then subtract points, but instead add points as usual and award points up to and including the median score. Points above the median score will not be reflected in your grade. Median score for each assignment will be posted on Slack after the grades are released.

The instructions for the revise and resubmit assignment are in the week 4 Assignments and Assessments section of Coursera. There is also a link there to submit the revised assignment. Do not resubmit an assignment to the original assignment!
The revised assignment is due on the last day of class at 11:59 p.m. EDT.

II. Course Schedule

Week 1: Introduction to Data Science Ethics, Top Misconceptions About Data Science Ethics, and Data Privacy

Learning Objectives:

Apply recommendations and perspectives about data privacy from case studies and literature presented.
Recognize instances of Zook's "10 simple rules of responsible big data research".
Identify and avoid misconceptions or common mistakes about data science ethics in given situations.
Identify different perspectives about data privacy from literature and case studies presented, and describe tensions between these perspectives.
Recognize and explain a data privacy problem using professional concepts and terminology.

Required Readings | Introduction to Data Science Ethics and Top Misconceptions About Data Science Ethics:

Loukides, M., Mason, H., & Patil, D. J. (2018). Doing good data science. In *Ethics and data science.* O'Reilly Media.   **>** Read Chapter 1 "Doing Good Data Science"

Floridi, L. & Taddeo, M. (2016). What is data ethics? *Philosophical Transactions of the Royal Society A, 374(2083).*https://doi.org/10.1098/rsta.2016.0360

Zook, M., Barocas, S., boyd, d., Crawford, K., Keller, E., Gangadharan, S.P., Goodman, A., Hollander, R., Koenig, B. A., Metcalf, J., Narayanan, A., Nelson, A., & Frank Pasquale. (2017). Ten simple rules for responsible big data research. *PLOS Computational Biology, 13*(3):1–11.

Required Readings & Viewing | Data Privacy:

Solove, D. J. (2011, May 15). Why privacy matters even if you have 'nothing to hide'. *Chronicle of Higher Education*, *15*.
https://www.chronicle.com/article/why-privacy-matters-even-if-you-have-nothing-to-hide/

Barocas, S., & Nissenbaum, H. (2014). Computing ethics: Big data's end run around procedural privacy protections. *Communications of the ACM, 57*(11): 31-33.

Bracken, K., & Harmon, A. (2010, April). Blood journey [Video]. The New York Times. https://www.nytimes.com/video/us/1247467672743/blood-journey.html

Madden, M., Gilman, M., Levy, K., & Marwick, A. (2017). Privacy, poverty, and big data: A matrix of vulnerabilities for poor Americans. *Washington University Law Review*, *95*.   **>** Read pages 53-67

Harwell, D. (2019, December 24). Colleges are turning students' phones into surveillance machines, tracking the locations of hundreds of thousands. *The Washington Post.* washingtonpost.com.

Week 2: Bias and Classification

Learning Objectives:

Identify and explain instances when data science incorporates harmful bias and may cause discriminatory outcomes or deepen inequalities
Identify and explain ethical problems that arise during routine classification work.
Demonstrate familiarity with selected tactics to promote fairness and mitigate harmful discrimination.

Required Readings & Viewing:

Gandy, O. (2012). Statistical surveillance: Remote sensing in the digital age. In K. Ball, K. Haggerty, K., & D. Lyon (Eds.). *Routledge Handbook of Surveillance Studies* (1st ed.) (pp. 125 - 132). Routledge. https://doi-org.proxy.lib.umich.edu/10.4324/9780203814949   **>** Read chapter by Oscar Gandy

American Civil Liberties Union. (2004). *Scary pizza* [Video]. Youtube.
https://www.youtube.com/watch?v=33CIVjvYyEk

Raji, D. (2020, December 10). How our data encodes systematic racism. *MIT Technology Review.*

Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016, June 6). Machine bias: Two drug possession arrests. *The Louisiana Weekly, 90*(38).   **>** Note: This reporting provides additional context related to the COMPAS data and risk assessment in the criminal justice system. It is not required but may be useful to add to your understanding.

[Recommended] Bao, M., Zhou, A., Zottola, S., Brubach, B., Desmarais, S., Horowitz, A., Lum, K., & Venkatasubramanian, S. (2022, April 28). It's COMPASlicated: The messy relationship between RAI datasets and algorithmic fairness benchmarks. *35th Conference on Neural Information Processing Systems.*

Hill, K. (2020, August 3). Wrongfully Accused By an Algorithm. *The New York Times.* https://www-proquest-com.proxy.lib.umich.edu/docview/2416163146 (with The New York Times subscription: https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html)   **>** Note: This incident in Detroit transpired after the field trip and interview with Tawana Petty was recorded. It is a very striking example of some of the unintended harmful consequences emerging from the deployment of facial recognition technology by police departments.

Citron, D. K., and Pasquale, F. (2014). The scored society: Due process for automated predictions. *Washington Law Review 89*(1).

Hanna, A., Denton, E., Smart, A., & Smith-Loud, J. (2020). Towards a critical race methodology in algorithmic fairness. *Proceedings of the 2020 conference on fairness, accountability, and transparency*, 501-512. https://dl.acm.org/doi/10.1145/3351095.3372826

Week 3: Data Provenance, Aggregation, and Trust

Learning Objectives:

Identify ethical issues raised by different sources of data.
Draw logical conclusions about problems with using publicly available data in data science work.
Draw logical conclusions about the problems of sampling in data science work.
Conduct an impact assessment for a hypothetical automation system that employs data science.

Required Readings:

Rieder, G. & Simon, J. (2016) Datatrust: Or, the political quest for numerical evidence and the epistemologies of Big Data. *Big Data & Society 3*(1), 1–6. https://doi.org/10.1177/2053951716649398

Onuoha, M. (2016). The point of collection. *Data & Society: Points,* https://medium.com/datasociety-points/the-point-of-collection-8ee44ad7c2fa

Martinez, E. & Kirchner. L. (2021, August 25). Secret bias hidden in mortgage-approval algorithms. *The Markup,* https://themarkup.org/denied/2021/08/25/the-secret-bias-hidden-in-mortgage-approval-algorithms

Melendez, S. & Pasternak, A. (2019, March 2). Here are the data brokers quietly buying and selling your personal information. *Fast Company.*

Kalluri, P. (2020, July 9). Don't ask if artificial intelligence is good or fair, ask how it shifts power. *Nature, 583, 169.* https://www.nature.com/articles/d41586-020-02003-2

Hao, Karen. (2022, April 22). A new vision of artificial intelligence for the people. *MIT Technology Review.*
https://www.technologyreview.com/2022/04/22/1050394/artificial-intelligence-for-the-people/

Week 4: Accountability and Governance

Learning Objectives:

Understand different data governance mechanisms and strategies.
Understand the utility and limits of algorithm audits and reverse engineering as accountability strategies.
Recognize and infer the limits of the transparency ideal.
Recognize and infer major challenges of conducting an external audit.
Discuss and explain the design of checklists and related tactics as a way to improve data science ethics in organizations.

Required Readings | Accountability & Governance:

Wallach, H. (2014, December 14). Big data, machine learning, and the social sciences: Fairness, accountability, and transparency. *Medium.*
https://hannawallach.medium.com/big-data-machine-learning-and-the-social-sciences-927a8e20460d
Please create a basic/free account to access if you can't access medium article.
Ananny, M., & Crawford, K. (2018). Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability. *new media & society, 20*(3), 973 - 989.
Sandvig, C., Hamilton, K., Karahalios, K., & Langbort, C. (2014). Auditing algorithms: Research methods for detecting discrimination on internet platforms. *Computational Culture.*
Diakopoulos, N. (2015). Algorithmic accountability. *Digital Journalism, 3*(3): 398-415.

Required Readings | Conclusion: Professional Ethics Oaths, Pledges, Checklists:

Loukides, M., Mason, H., & Patil, D. J. (2018). Of oaths and checklists. In *Ethics and Data Science.* O'Reilly Media. **>** Read Chapter 2, Of oaths and checklists

III. Further Readings/Listenings

Week 1: Introduction to Data Science Ethics, Top Misconceptions About Data Science Ethics, and Data Privacy

Further Readings/Listenings: Introduction to Data Science Ethics & Top Misconceptions About Data Science Ethics

Ananny, M. (2016). Toward an ethics of algorithms : Convening observation , probability , and timeliness. *Science, Technology, & Human Values, 41*(1):93–117.

Brey, P. A. E. (2012). Anticipating ethical issues in emerging IT. *Ethics and Information Technology, 14,* 3015-317.

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

Labbé, C. (Host). (2019, May 2). Solon Barocas on teaching ethics in data science (Episode 8) [Audio podcast episode]. In *Good Code.* Cornell Tech.

Metcalf, J., Moss, E., & boyd, d. (2019). Owning ethics: Corporate logics, Silicon Valley, and the institutionalization of ethics. *Social Research: An International Quarterly, 82*(2):449–76.

Moor, J. H. (2005). Why we need better ethics for emerging technologies, *Ethics and Information Technology, 7,* 111-119.

O'Neil, C. (2014). On being a data skeptic. O'Reilly Media, Inc. https://learning.oreilly.com/library/view/on-being-a/9781491947227/

Salganik, M. J. (2019). Ethics. In *Bit by bit: Social research in the digital age* (pp. 281-354). Princeton University Press.https://www.bitbybitbook.com/en/1st-ed/ethics/

Singer, N. (2018, February 12). Tech's ethical 'dark side': Harvard, Stanford and others want to address it. *The New York Times.*

Further Readings/Listenings: Data Privacy (general)

Cate, F. H. (2006). The failure of fair information practice principles. In J. K. Winn, & G. Howells (Eds.), *Consumer protection in the age of the "information economy"* (pp. 341 - 433). Taylor & Francis Group.   **>** The following sections are likely most relevant: The Evolution of Fair Information Practice Principles, 343-346 (stop at "The OECD Guidelines"); The FTC Privacy Principles, 350-351 (stop at "The APEC Privacy Framework"); The Focus on Consumer Control/The Focus on Notice and Choice/Many Notices that Few People Read/Notices that Few People Understand/The Cost of Choice/The Benefits of No Choice/The Illusion of Choice, 354-365 (stop at "National Law in a Global World"); A Modest Proposal, 367-372 (stop at "Conclusion")

Cate, F. H. and Mayer-Schonberger, V. (May 20, 2013). Notice and consent in a world of big data. *International Data Privacy Law 3*(2) , 67–73.

Helm, P. (2018). Treating sensitive topics online: A privacy dilemma. *Ethics and Information Technology 20*(4), 303–13.

Labbé, C. (Host). (2019, March 26). Helen Nissenbaum on Post-Consent Privacy. (Episode 2) [Audio podcast episode]. In *Good Code.* Cornell Tech.

Narayanan, A., & Shmatikov, V. (2010). Myths and fallacies of "personally identifiable information." *Communications of the ACM 53*(6), 26.

Nissenbaum, H. (2010). *Privacy in context: Technology, policy, and the integrity of social life*. Stanford Law Books.

Sambasivan, N., Checkley, G., Batool, A., Ahmed, N., Nemer, D., Gaytán-Lugo, L. S., Matthews, T., Consolvo, S., & Churchill, E. (2018). "Privacy is not for me, it's for those rich women": Performative privacy practices on mobile phones by women in South Asia. *USENIX Symposium on Usable Privacy and Security,* 127-142. https://nithyasambasivancom.files.wordpress.com/2018/06/performativeprivacy_soups.pdf

Schermer, B. W., Custers, B. H. M., & Van der Hof, S. (2014). The crisis of consent: How stronger legal protection may lead to weaker consent in data protection. *Ethics and Information Technology, 16,* 171-182.

Solove, D. J. (2013). Introduction: Privacy self-management and the consent dilemma. *Harvard Law Review 126*(7), 1880–1903.   **>** The following section is likely most relevant: I. privacy self-management 1880-1893

Further Readings/Listenings: Data Privacy (genetics domain example)

Allyse M. A., Robinson, D.H., Ferber, M. J., & Sharp, R. R. (2018). Direct-to-consumer genetic testing 2.0: Emerging models of direct-to-consumer genetic testing. *Mayo Clinic Proceedings, 93*(1), 113-20

Kowal, E., Radin, J., & Reardon, J. (2013). Indigenous body parts, mutating temporalities, and the half-lives of postcolonial technoscience. *Social Studies of Science 43*(4), 465-483.

Mcguire, A. L., & Beskow, L. M. (2010). Informed consent in genomics and genetic research. *Annual Review of Genomics and Human Genetics, 11,* 361–81.

Messner, D. A. (2011). Informed choice in direct-to-consumer genetic testing for Alzheimer and other diseases: Lessons from two cases. *New Genetics and Society, 30,* 59-72. https://doi-org.proxy.lib.umich.edu/10.1080/14636778.2011.552300

Udesky, L. (2011). The ethics of direct-to-consumer genetic testing. *The Lancet 376*(9750), 1377–78.

Week 2: Bias and Classification

Angwin, J., Larson, J., Kirchner, L., & Mattu, S. (2017, April 5) Minority neighborhoods pay higher car insurance than white neighborhoods with the same risk. ProPublica.

Bender, E., Gebru, T., McMillan-Major, A., & Shmitchell. (2021). On the dangers of stochastic parrots: Can language models be too big? *FAccT '21.* https://dl.acm.org/doi/pdf/10.1145/3442188.3445922

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new Jim Code*. Polity Press.

Bowker, G. C., & Star, S. L. (1999). Some tricks of the trade in analyzing classification, In *Sorting Things Out: Classification and Its Consequences* (pp. 33-50). MIT Press.

Boyd, d., Levy, K., & Marwick, A. (2014). The networked nature of algorithmic discrimination. *Open Technology Institute.*

Buolamwini, J. & Gebru, T. (2017). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research, 81,* 77-91.

- Also see Buolamwini, J. (2016, November). [How I'm fighting bias in algorithms](https://www.ted.com/talks/joy_buolamwini_how_i_m_fighting_bias_in_algorithms) [Address]. TEDxBeaconStreet, Brookline, MA. https://www.ted.com/talks/joy_buolamwini_how_i_m_fighting_bias_in_algorithms

Chen, L., Ma, R., Hannák, A., & Wilson, C. (2018). [Investigating the impact of gender on rank in resume search engines.](#) *Proceedings of the 2018 ACM Conference on Computer-Human Interaction (CHI'18).*
Eubanks, V. (2018). *[Automating inequality: How high-tech tools profile, police, and punish the poor.](#)* St. Martin's Press.
Haimson, O. L., & Hoffmann, A. L. (2016). [Constructing and enforcing 'authentic' identity online: Facebook, real names, and non-normative identities.](#) *First Monday, 21,* 6.
Noble, S. U. (2018). *[Algorithms of oppression: How search engines reinforce racism.](#)* New York University Press.
Sandvig, C. (2015). [Seeing the sort: The aesthetic and industrial defense of 'The Algorithm.'](#) *Media-N: Journal of the New Media Caucus 10*(3).

Week 3: Data Provenance, Aggregation, and Trust

Allen, M. (2018, July 17). Health insurers are vacuuming up details about you — and it could raise your rates. ProPublica. https://www.propublica.org/article/health-insurers-are-vacuuming-up-details-about-you-and-it-could-raise-your-rates
Benjamin, R. (2021). [Race to the Future? Reimagining the Default Settings of Technology & Society](#) [Video]. AAAS Annual Meeting. https://www.youtube.com/watch?v=8IJKA8ciZCg **>** watch first 12:30 minutes
Franz, N. M. (2018). To increase trust, change the social design behind aggregated biodiversity data. *Database.* https://academic-oup-com.proxy.lib.umich.edu/database/article/doi/10.1093/database/bax100/4791171
Martin, K.E. (2015, June). Ethical issues in the big data industry. *MIS Quarterly Executive, 14*(3), 67 - 85. https://www.researchgate.net/profile/Kirsten-Martin-2/publication/340465839_Ethical_Issues_in_the_Big_Data_Industry/links/61b753e44b318a6970db2f70/Ethical-Issues-in-the-Big-Data-Industry.pdf
McFarland, M. (2012). Ethical implications of data aggregation. Makkula Center for Applied Ethics at Santa Clara University. https://www.scu.edu/ethics/focus-areas/internet-ethics/resources/ethical-implications-of-data-aggregation/

Week 4: Accountability and Governance

Further Readings/Listenings | Accountability & Governance:

Boyd, d. (2017) Toward Accountability: Data, Fairness, Algorithms, Consequences. Data and Society: Points. [blog post]

D'Ignazio, C. and Klein, L.F. (2020). The power chapter. In *Data Feminism* (pp. 21-47). MIT Press. https://direct-mit-edu.proxy.lib.umich.edu/books/book/4660/Data-Feminism

Green, B. (2019, December). "Good" isn't good enough. *AI for Social Good workshop,* NeurIPS, Vancouver, Canada.

Karppi, T., & Crawford, K. (2015). Social media, financial algorithms and the hack crash. *Theory, Culture & Society, 33* (1), 73–92.

Pasquale, Frank. (2015). *The black box society: The secret algorithms that control money and information.* Harvard University Press.   **>** Read the following chapters: Ch. 1: The Need to Know, Ch. 6: Toward an Intelligible Society.

Pasquale, Frank. (2006). Rankings, reductionism, and responsibility. Cleveland State Law Review, 54(1), 115-139.

Song, C., & Shmatikov. (2019). Auditing text generation models. *KDD '19.* https://dl.acm.org/doi/pdf/10.1145/3292500.3330885

Further Readings/Listenings | Conclusion: Professional Ethics Oaths, Pledges, Checklists:

Loukides, M., Mason, H., & Patil, D. J. (2018). Data's Day of Reckoning. In *Ethics and Data Science.* O'Reilly Media. > Read Chapter 4, Data's day of reckoning

Simonite, T. (2018, February 8). Should data scientists adhere to a Hippocratic Oath? *Wired*. https://www.wired.com/story/should-data-scientists-adhere-to-a-hippocratic-oath/

United Nations. (1948). *Universal Declaration of Human Rights*. https://www.un.org/en/universal-declaration-human-rights/

IV. Additional Course Policies

Academic Integrity

Collaboration

UMSI strongly encourages collaboration while working on some assignments, such as work on team projects and interpreting reading assignments as a general practice. Active learning is effective. You must, however, write your individual assignment submissions on your own, in your own words. You should not collaborate on quizzes. Read the instructions carefully and request clarification about collaboration when in doubt.

Plagiarism

Unless otherwise specified in an assignment, all submitted work must be your own original work. Any excerpts, statements, or phrases from the work of others must be clearly identified as a quotation, and a proper citation provided (inline and reference list). Ideas and concepts from

course or external materials used in assignment submissions must also be properly cited (inline and in a reference list). If you do not cite the source of the ideas or quotations you use, this is considered plagiarism.

In this course, an assignment containing plagiarized material will receive zero points. This applies whether the plagiarism is intentional or inadvertent. Any violation of the School's policy on Academic and Professional Integrity (stated in the MADS Student Handbook) will also be reported to UMSI Student Affairs.

The University Library also offers information about academic integrity and how you can protect yourself. If you are unsure about whether a passage in your writing constitutes plagiarism, you are encouraged to seek help from the teaching team or from the Sweetland Writing Center. Be sure to plan sufficiently ahead in your writing so that you can receive and incorporate feedback if you are uncertain about the boundaries of plagiarism.

AI-generated text tools: ChatGPT is a new AI product that has become very popular over the last few months. It is a generative AI tool that uses large language models to produce answers and responses to questions. There are many potentially productive uses of ChatGPT (and likely some important ethical questions), but the use of ChatGPT or any other AI-generated text tool to write text for class assignments is not allowed. Any assignments found to have used ChatGPT to write text for course assignments will earn zero points.

Accommodations

Refer to the Accommodations for Students with Disabilities section of the UMSI Student Handbook. Information regarding SSD, the services available to students with disabilities, and the rights and responsibilities of students with disabilities is available on the Services for Students with Disabilities website. If you have questions about obtaining authorized accommodations, please contact the MADS Academic Advising Team at umsi.advising.mads@umich.edu.

Library Access

Refer to the U-M Library's information sheet on accessing library resources from off-campus. For more information regarding library support services, please refer to the U-M Library Resources section of the UMSI Student Handbook (access to the Student Orientation course required).

Student Mental Health

Refer to the University's Resources for Stress and Mental Health website for a listing of resources for students.

Student Services

Refer to the Introduction to UMSI Student Life section of the UMSI Student Handbook (access to the Student Orientation course required).

V. Acknowledgements