



Communication Lead Description

- Ensures all communication deliverables (document, minutes, agendas, ppts, reports) **meet requirements**
- Acts as **point of contact for SEW**
- Disseminates communication **reminders** to team
- Encourages team to incorporate **ethical** framework and **creative & critical** thinking



Ethical Considerations for Data Professionals

Dr. Sarah Egan Warren, Class of 2024



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CLASS ONE THEME: FRAMEWORKS



What is Data Ethics

- YOUR definition



What is Data Ethics

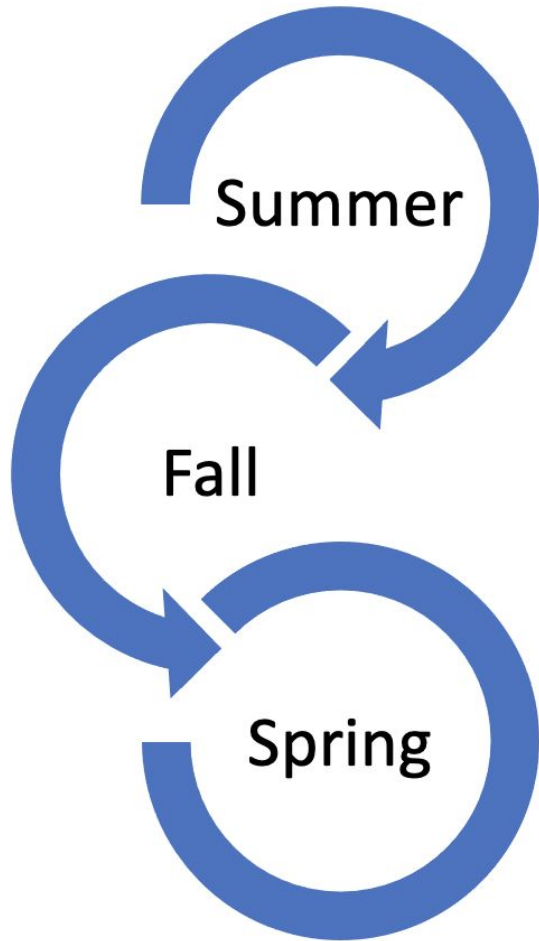
- “Data ethics can be defined as the branch of ethics that **studies and evaluates moral problems related to data** (including generation, recording, curation, processing, dissemination, sharing and use), **algorithms** (including artificial intelligence, artificial agents, machine learning and robots) **and corresponding practices** (including responsible innovation, programming, hacking and professional codes), **in order to formulate and support morally good solutions** (e.g. right conducts or right values).”
 - Luciano Floridi and Mariarosaria Taddeo, Royal Society Publishing
- “Data ethics encompasses the moral obligations of gathering, protecting, and using personally identifiable information and how it affects individuals.”

- “Data ethics refers to the principles behind how organizations gather, protect, and use data.” **Data Camp**
- “*Data Ethics* are the norms of behavior that promote appropriate judgments and accountability when acquiring, managing, or using data, with the goals of protecting civil liberties, minimizing risks to individuals and society, and maximizing the public good.”
Federal Data Strategy Data Ethics Framework
- “Data ethics encompasses the moral obligations of gathering, protecting, and using personally identifiable information and how it affects individuals.” **Harvard Business School**
- “Big data ethics also known as simply data ethics refers to systemizing, defending, and recommending concepts of right and wrong conduct in relation to data, in particular personal data.” **Wikipedia**
- “Data ethics is the study of the ethical principles and values that guide the collection, use, and sharing of data.” **Bard**
- “Data ethics refers to the moral principles and guidelines governing the responsible and just collection, use, sharing, and management of data. It involves considering the impact of data-driven actions on individuals, society, and privacy, while striving to minimize potential harms and ensure fairness, transparency, and accountability throughout the data lifecycle.”
ChatGPT



Agenda

- Overview & Expectations
- Revisiting Ethical Case Studies from Communication Week
- Frameworks
- Assignments



Ethical Considerations for Data Professionals

- Persuasion (ethos/logos/pathos)
 - [Critical & Creative Thinking](#)
 - Ethical Data Storytelling (speaking)
 - How to be an Anti-Racist Data Scientist
 - Ethics Case Studies
-
- Frameworks
 - Guest Speakers
 - Open Pedagogy Resource: Data Ethics Repository
 - Practicum considerations/One Pager
 - *Persuasion*
 - [Critical & Creative Thinking](#)
 - *Ethical Data Storytelling (speaking & writing)*
-
- Bias
 - *Persuasion*
 - [Critical & Creative Thinking](#)
 - *Ethical Data Storytelling (speaking & writing)*

ECDP Classes Fall 1

Class 1	Aug 23	Lecture
Class 2	Aug 25	Guest Speaker Zoom (Emily Hadley)
Class 3	Aug 30	Lecture, Team
Class 4	Sept 11	Lecture, Small Group Sharing
Class 5	Sept 14	Guest Speaker Zoom (Patrick Hall)
Final	Sept 27-28	Practicum Team Meetings with SEW

Revisit Communication Week

Ethical Case Studies

What were the themes from the cases?

- Automation
- Autonomy
- Capabilities
- Censorship
- Consequentialism
- Contextual Integrity
- Determinism
- Diversity
- Downstream Responsibility
- Fairness
- Fallibility
- Foundations of legitimacy

- Inequality
- Irreconcilability
- Neutrality
- Paternalism
- Privacy
- Representational Harms
- Research Ethics
- Rhetoric
- Rights
- Secrecy
- Sovereignty
- Transparency

Automation: AI still needs humans

Autonomy: individuals ability to make decisions for self

Capabilities: AI designed to save time

Censorship: content moderation?

Consequentialism: do the ends justify the means VS somethings are impermissible even if a good outcome

Contextual integrity: appropriateness use of an individual's information according to how well that use conforms to the reasonable expectations the individual had when consenting to share the information.

Determinism: all events are causally inevitable... all events are determined completely by previously existing causes

Diversity variety of people/ideas

Downstream Responsibility once it leaves your hands, you may not have control
Fairness: equal opportunity or equality of outcomes

Fallibility: what is produced by algorithms are PROBABILITIES not certainties.

Foundations of legitimacy: claim that users WANTED the feature.

Inequality: can come from skewed data collection.

Irreconcilability: holding two competing principles

Neutrality: value judgements about what is good/bad

Paternalism: Do intentions matter? Helping with good ends. How to balance freedom and outcomes

Representational Harm: categorizing could harm participant, undermine identity

Research ethics: Human subjects, IRB

Rhetoric: words matter

Rights: balance benefit and rights

Secrecy: some secrets are needed to protect from bad actors?

Sovereignty: issue of citizenship

Transparency: open to sharing the ends, means, and thought processes about a project

Framework #1

The Five Cs:
Five framing guidelines
to help you think about
building data products

By DJ Patil, Hilary Mason, and Mike Loukides,
2018

<https://www.oreilly.com/radar/the-five-cs/>

The Five Cs

Consent

“You can’t establish trust between the people who are providing data and the people who are using it without agreement about what data is being collected and how that data will be used. **Agreement starts with obtaining consent to collect and use data.**”

Clarity

“You can’t really consent to anything unless you’re **told clearly what you’re consenting to.** Users must have clarity about what data they are providing, what is going to be done with the data, and any downstream consequences of how their data is used.”

Consistency & Trust

“Trust requires consistency over time. You can’t trust someone who is unpredictable.”

Control & Transparency

“You must be able to understand what is happening to your data... All too often, users have no effective control over how their data is used. They are given all-or-nothing choices, or a convoluted set of options that make controlling access overwhelming and confusing.”

Consequences

“Risks can never be eliminated completely. However, many unforeseen consequences and unknown unknowns could be foreseen and known, if only people had tried. All too often, unknown unknowns are unknown because we don’t want to know.”

Influential Practices for The Five Cs

Consent

“Ask whether appropriate and necessary consent has been provided.”

Clarity

“Inform users what they’re consenting to.”

Consistency & Trust

“Restoring trust requires a prolonged period of consistent behavior.”

Control & Transparency

“Give users greater control of their data.”

Consequences

“Ask whether the data that is being collected could cause harm to an individual or a group.”

Framework #2

PRACTICE

Data Science Ethics

<https://datascienceethics.com/data-science-ethics-in-practice/>

P.R.A.C.T.I.C.E.

P rotect Privacy	Abide by privacy regulations, respect subjects, safeguard information.
R etain Responsibility	Rectify issues and communicate clearly.
A nticipate Adversaries	Minimize potential harm by thinking of what could be abused
C ollect Carefully	Only collect what you will use, document biases
T rain Transparently	Be open about assumptions and data modifications
I ncorporate Inclusivity	Gather varied perspectives
C onsider Context	Adjust sensitivity based on potential downstream implications
E ncode Equity	Use algorithms fairly and with as little bias as possible

Framework #3

DELICATE

IT'S A DELICATE ISSUE

[Privacy and Analytics - it's a DELICATE issue: A Checklist for Trusted Learning Analytics](#)

INFLUENTIAL PRACTICES

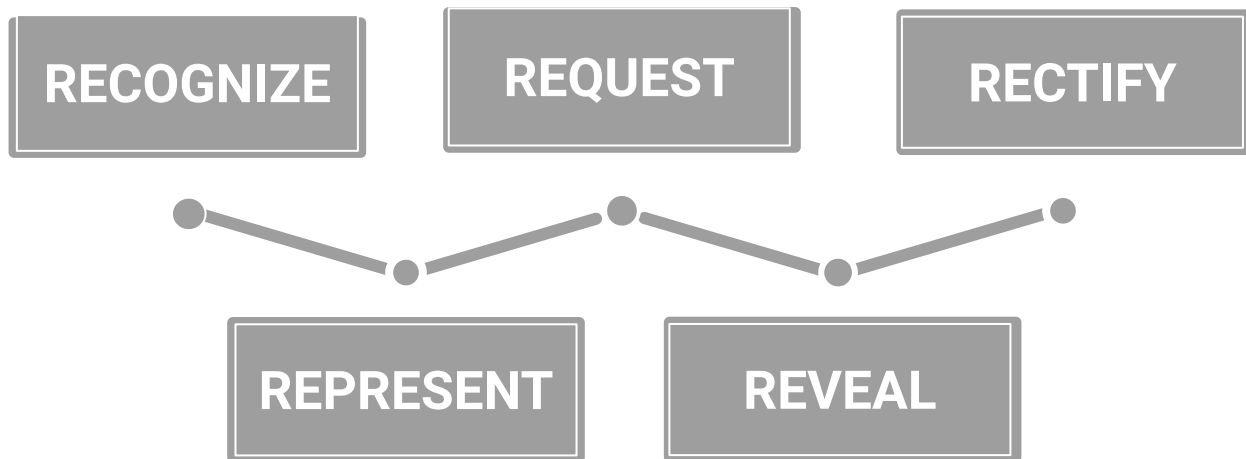
D	Determination: decide on objectives, rights, and processes
E	Explain: lay out transparent data lifecycle steps and responsibilities
L	Legitimate: determine authorizations and allowances
I	Involve: support participatory design, stakeholder input, and user agency
C	Consent: clearly communicate about data collection and allow user decision-making
A	Anonymize: use anonymization and aggregation to protect user privacy
T	Technical: monitor privacy processes and security standards
E	External: oversee external partners and their compliance with ethical standards

Framework #4

The Five Rs of Data Science

Curated & Created by Brooke Belcher
specifically for the Institute for Advanced
Analytics with guidance by Dr. Sarah Egan
Warren and input from current students and
alumni, 2022

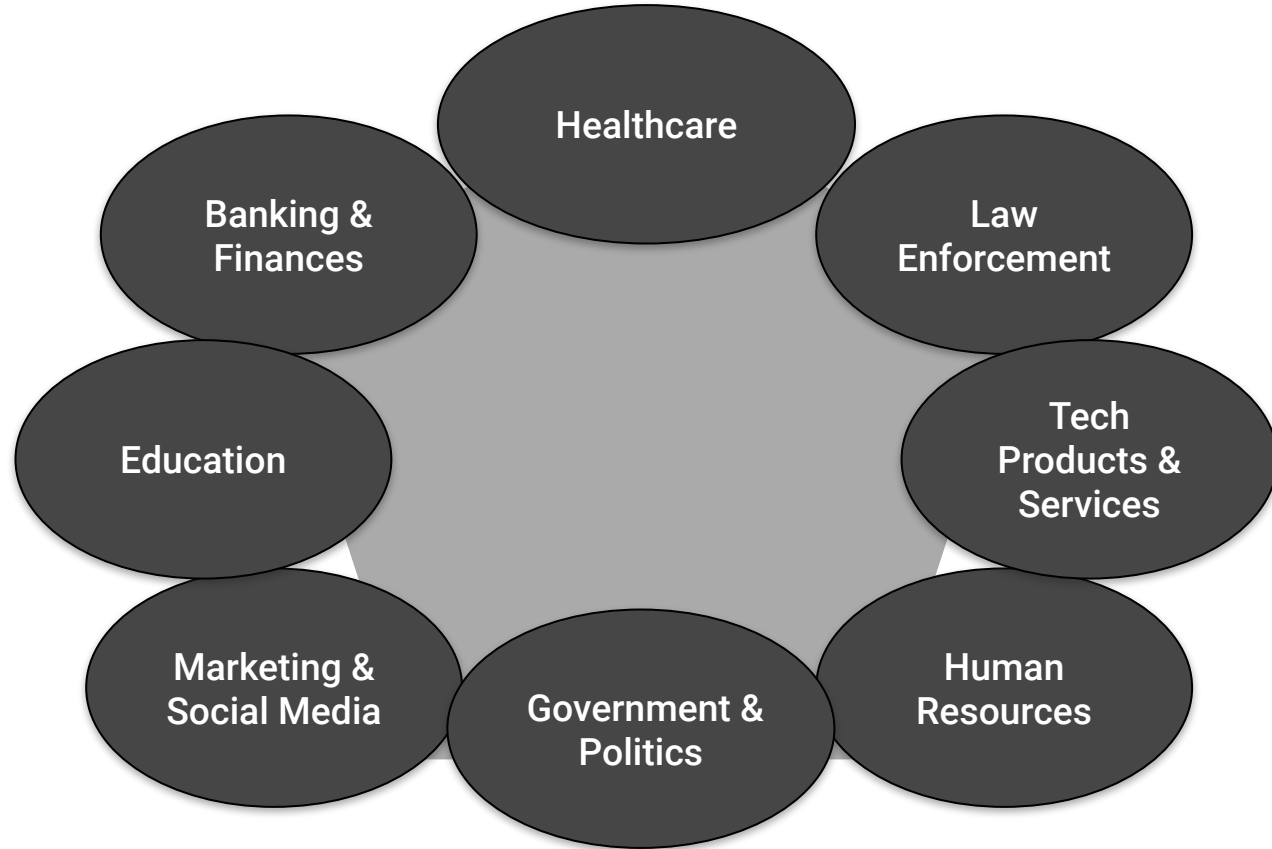
THE 5 Rs OF RESPONSIBLE DATA SCIENCE



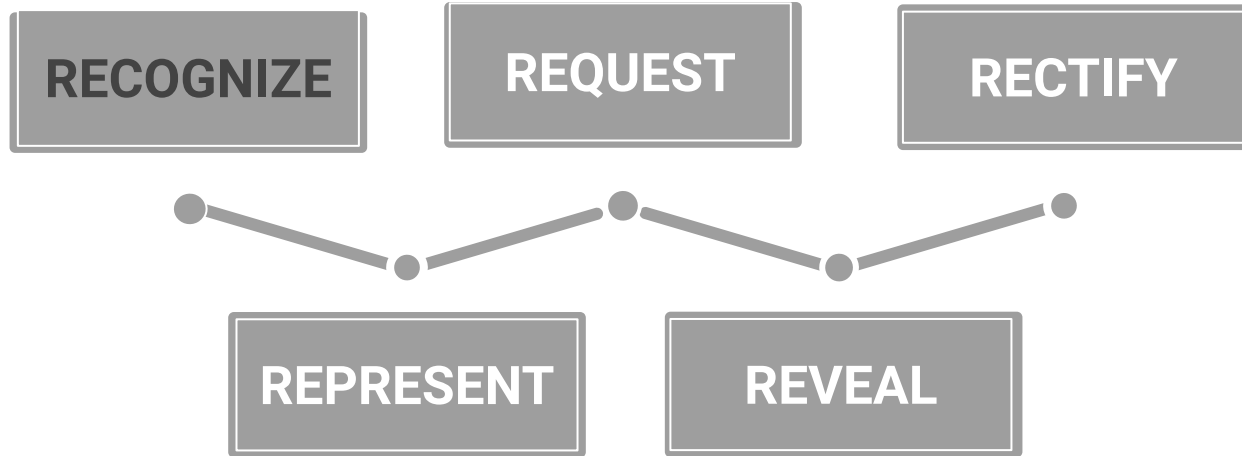
Biased algorithms impact products, outcomes, & people

Algorithmic Bias in
the Real World

The Secret Bias
Hidden in Mortgage
Approval
Algorithms



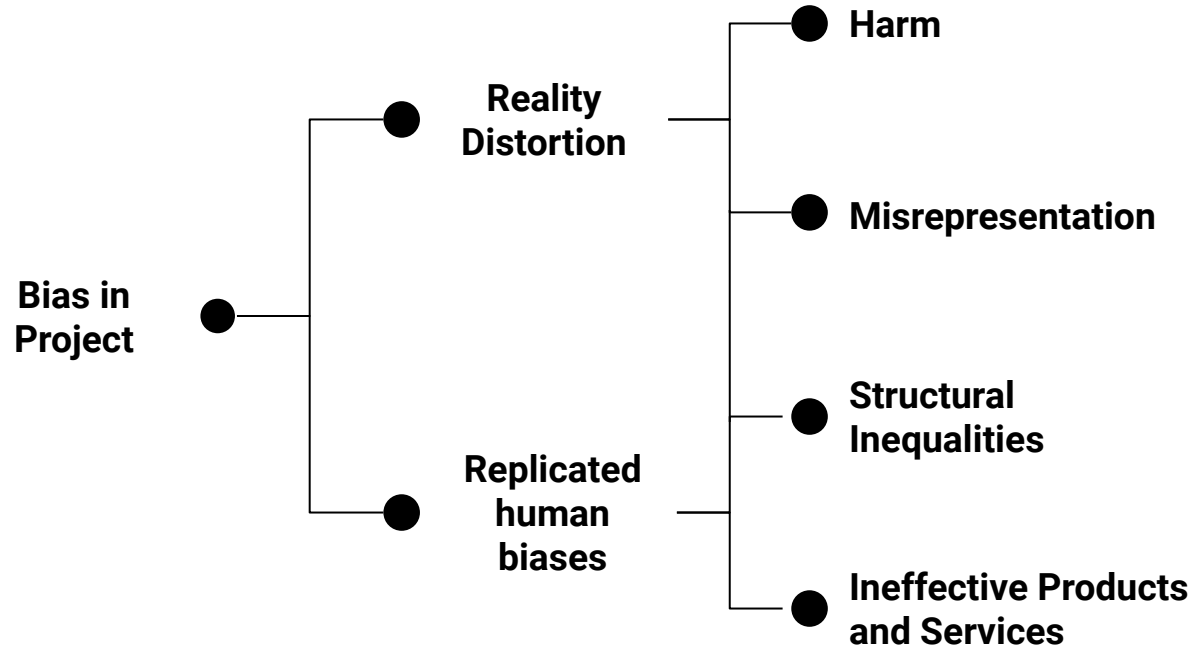
THE 5 Rs OF RESPONSIBLE DATA SCIENCE



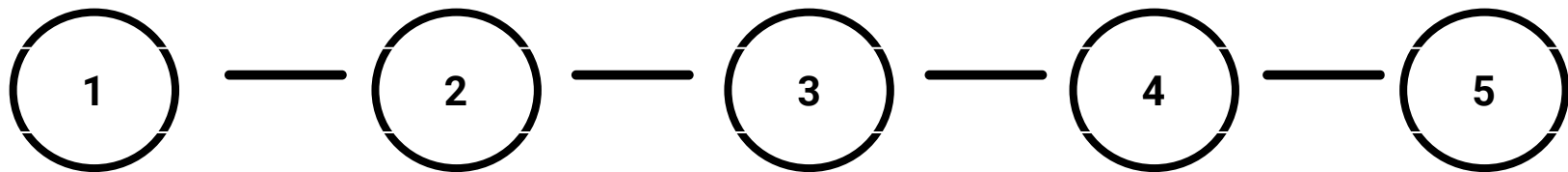
Recognizing bias and problems in data science projects has to be one of the first steps towards change

Recognize: identify bias & potential problems with diversity and user participation

Recognize bias because of wide-reaching consequences



INFLUENTIAL PRACTICES: Reduce bias



**Check
accuracy &
quality for
diverse
communities**

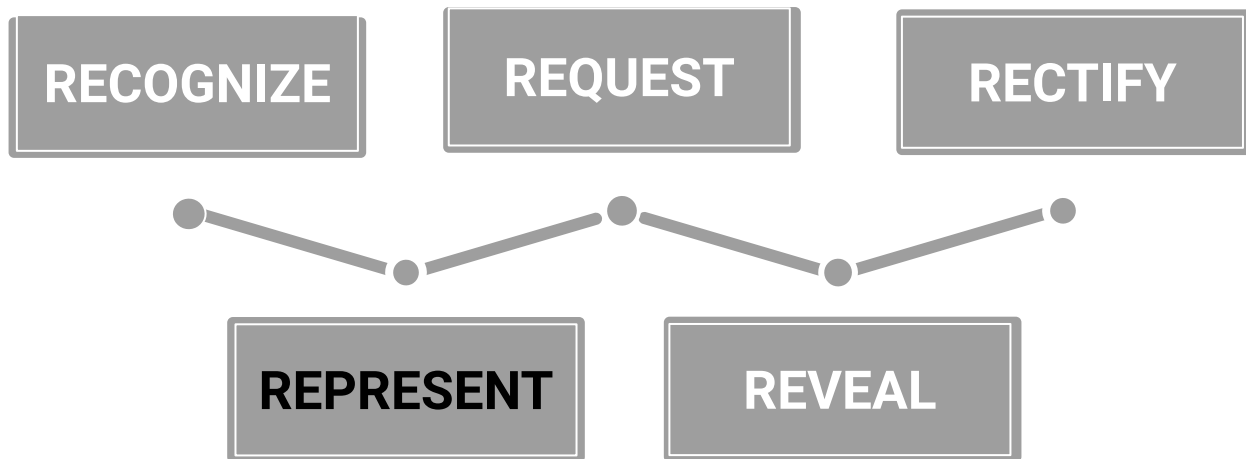
**Use data
sets that
match
diverse
users**

**Involve
diverse users
in product or
algorithm
testing**

**Plan for
human
oversight
of
algorithms**

**Inform
participants
about data &
processes**

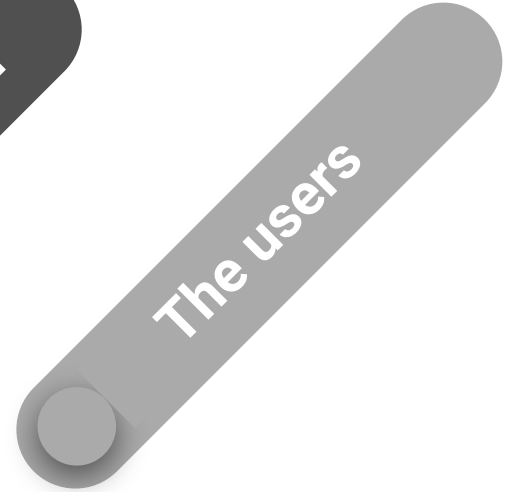
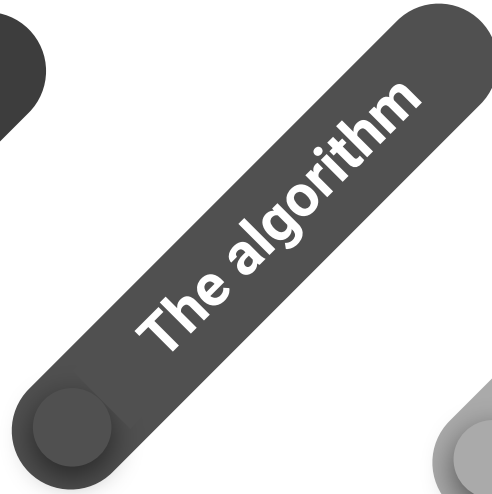
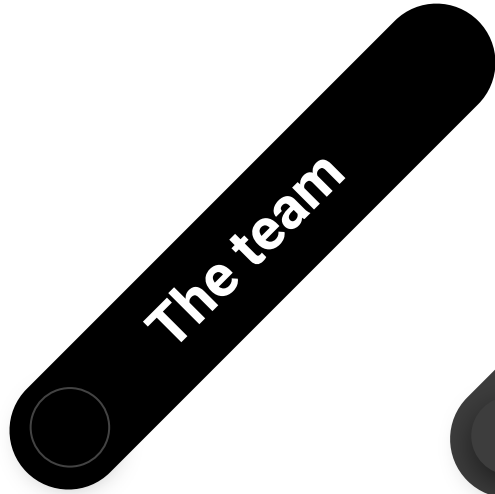
THE 5 Rs OF RESPONSIBLE DATA SCIENCE



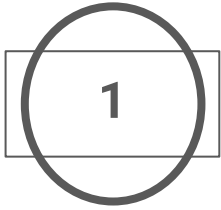
Instead of focusing on the negative, how can the design / process promote fairness and equity?

Represent: promote diversity, participatory design, and user advocacy

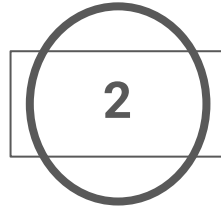
Bias/Lack of Diversity can have negative IMPACT



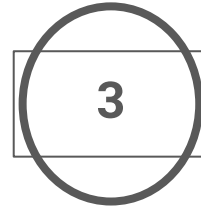
INFLUENTIAL PRACTICES: Encourage diversity



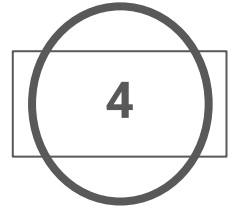
**Assemble diverse,
interdisciplinary
teams to face
diverse problems**



**Increase
practitioner
diversity in
analytics & tech
fields**

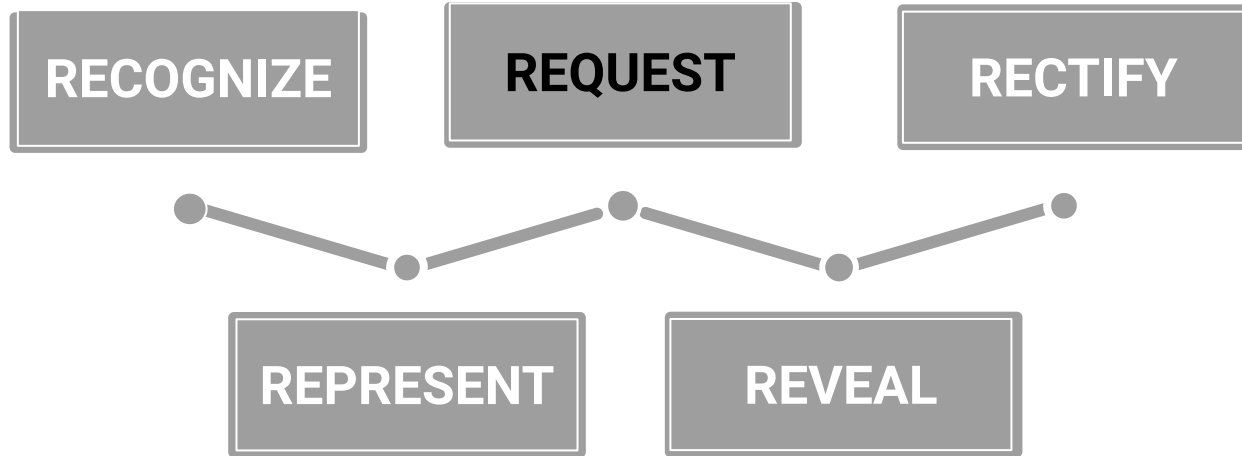


**Use participatory
design & research
to involve
under-represente
d people**



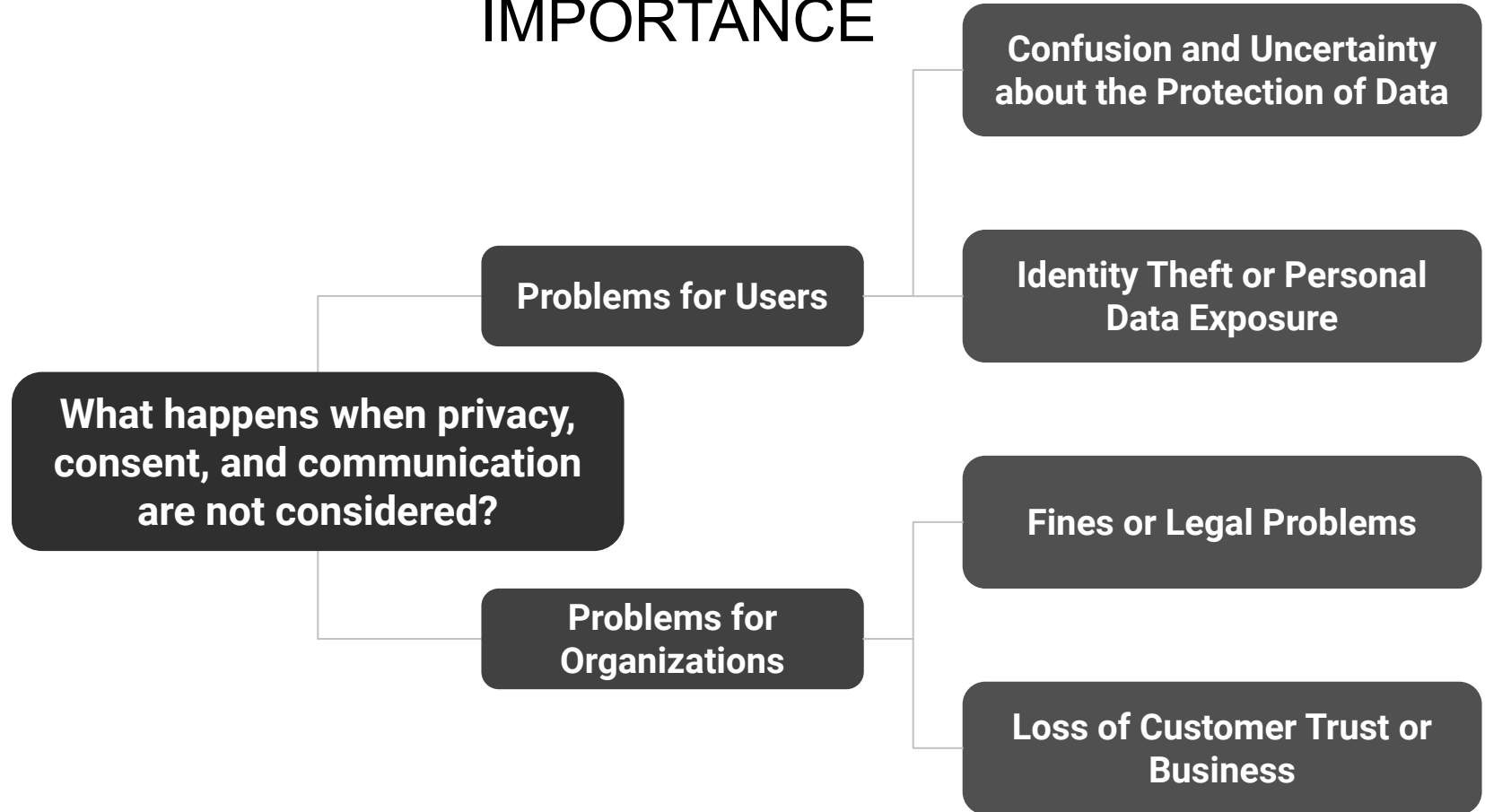
**Emphasize the
humanity of
users while
protecting their
privacy**

THE 5 Rs OF RESPONSIBLE DATA SCIENCE



Request: ask for clear consent to avoid privacy violations, user consent issues, and communication errors

IMPORTANCE



INFLUENTIAL PRACTICES

Identify Privacy, Consent, and User Communication Issues Early

**Gaps in Privacy
System**

**Reidentification of
Data**

**Unclear or
Nonexistent
Authorization**

**Non-existent or
Confusing
Consent**

**Lack of
Algorithmic
Transparency**

**Targeted
Marketing that
Exploits Users**

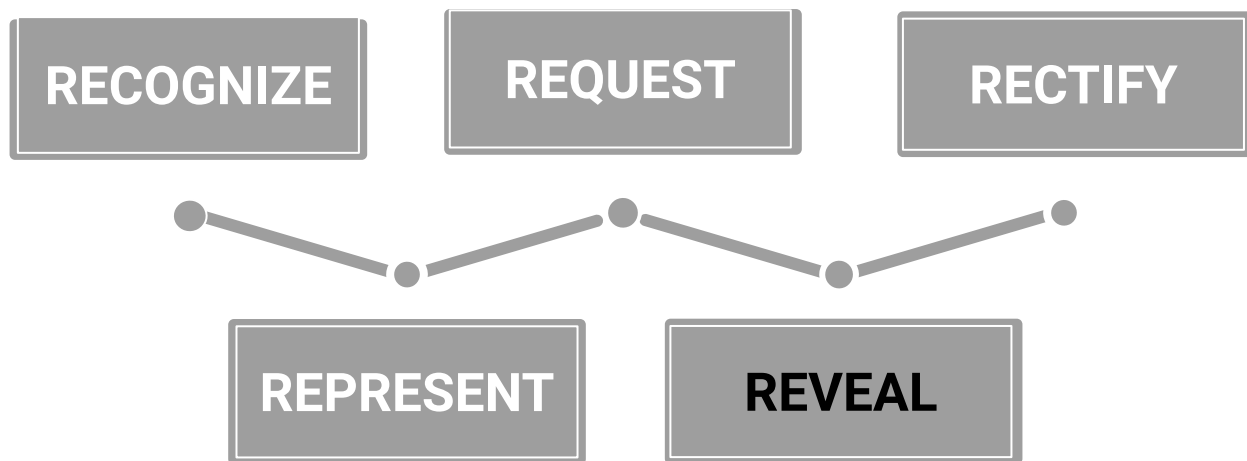
**User Confusion
about Data
Collection & Use**

**Data Lifecycle
Management
Problems**

**Responsibility
Management**

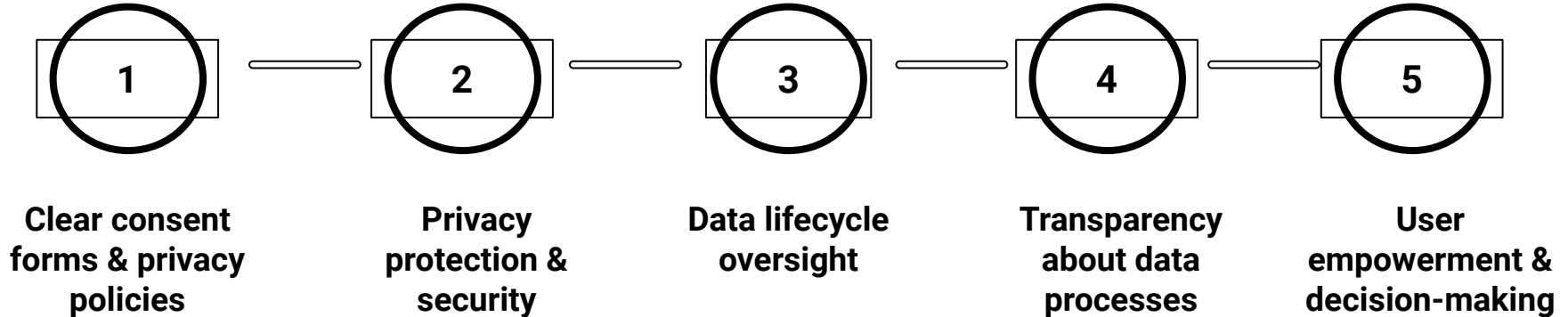
**Legal or
Organizational
Violations**

THE 5 Rs OF RESPONSIBLE DATA SCIENCE

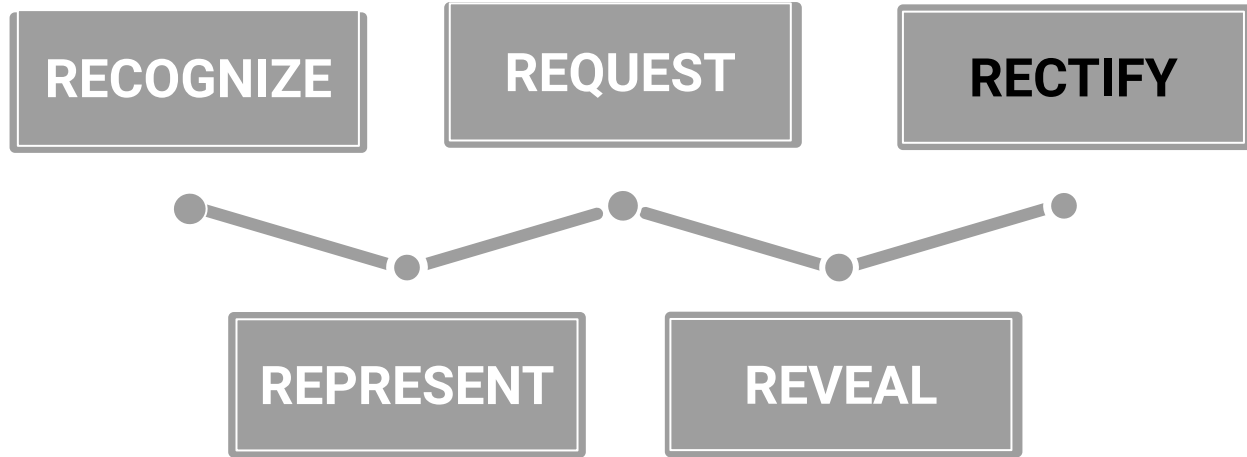


Reveal: act with transparency, regularity, and trustworthiness

IMPORTANCE: gain trust, be transparent, communicate



THE 5 Rs OF RESPONSIBLE DATA SCIENCE



Rectify: make decisions, change processes, reduce harm, and promote benefits

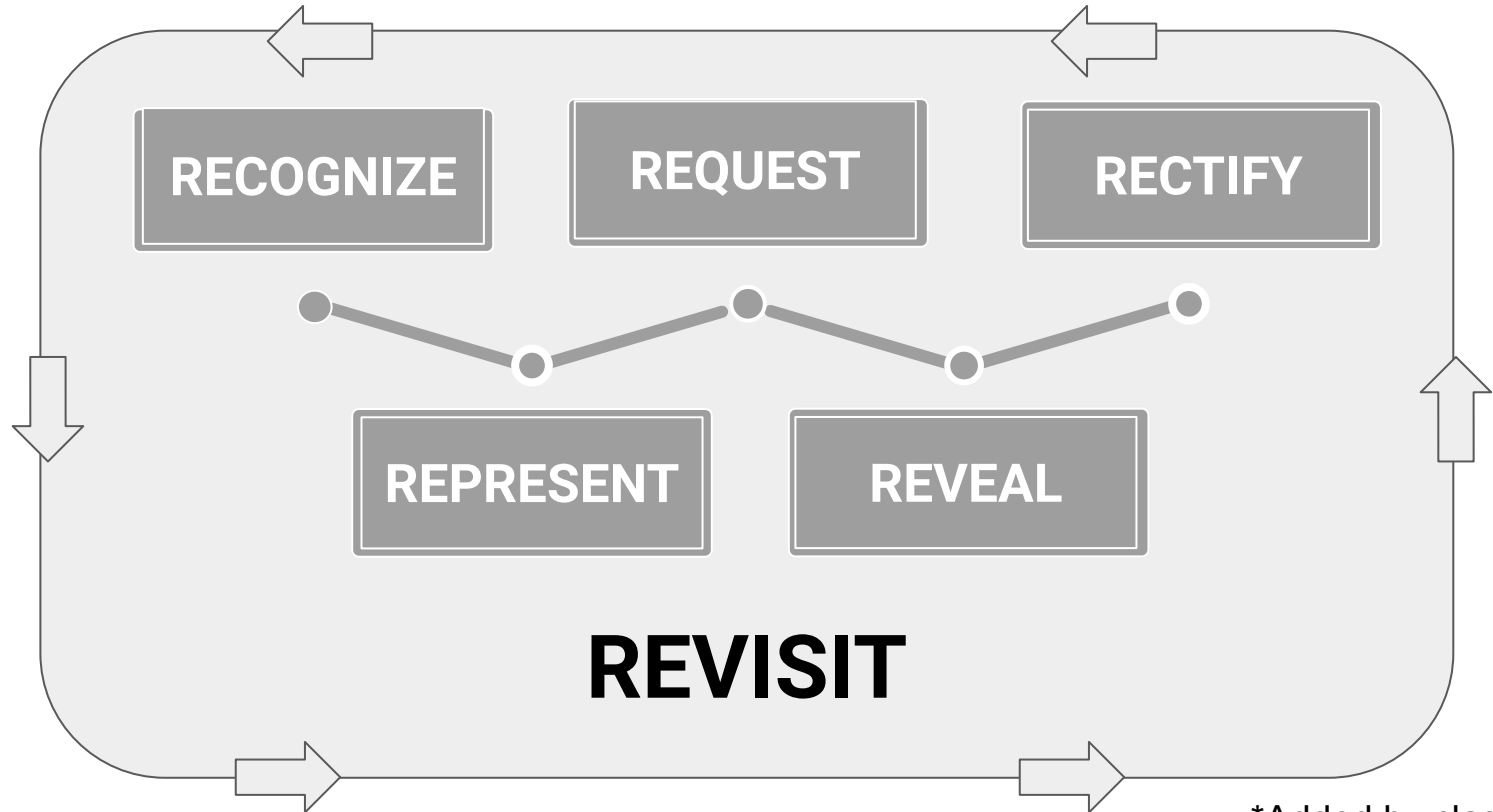
**How do data scientists make ethical decisions,
change unethical systems, and promote benefits
within various industries?**

A Framework for Ethical Decision-making

Rectify

Recognize	<ul style="list-style-type: none">• What processes are in place to identify bias in the data?• What potential problems with the data or algorithm can you identify that could harm or misrepresent users?• How will problems identified later in the process be rectified?
Represent	<ul style="list-style-type: none">• How is diversity encouraged on your team?• How is diversity encouraged in product testing, user participation, and training data?• How is participatory design or user advocacy included in the project or organizational objectives?
Request	<ul style="list-style-type: none">• How are privacy concerns and risks throughout the data lifecycle addressed?• Who is responsible for managing privacy, transparency, and clear communication in various project phases?• How are complaints about consent, data collection, privacy violations, etc. handled?
Reveal	<ul style="list-style-type: none">• How are you making the data collection and algorithm development process transparent to team members and stakeholders?• Are consent forms and privacy policies readable, concise, and clear about data collection risks and security standards? Have these consent forms and privacy policies been tested by users?

THE 6* Rs OF RESPONSIBLE DATA SCIENCE



*Added by class of 2023

Assignments

Individual and Team Assignments

ECDP Assignments Fall 1

Individual	Practicum Team
8 contributions to the Data Ethics Repository *2 due weekly by 8am 8/30, 9/6, 9/13, 9/20	One Pager Ethics Framework/Considerations for YOUR practicum project
Questions for Guest Speakers Emily Hadley & Patrick Hall	10-minute team meeting about One Pager with SEW Scheduled for Sept 27/28
Informal small group discussions	
Participation	

Data Ethics Repository ([DER SHEET](#))

The Data Ethics Repository

HomeAboutTopicsMedia Type

Code of Ethics

Resources that discuss holding oneself or group accountable for their actions.

Panel Discussion: Data Ethics in the Stories We Tell

May 4, 2023 by [Inbressa](#)

Author: N/A; Publisher: ParsonsTKO; Publication Year: 2021. The following video discusses how data storytelling is essential for any good data scientist. This makes it even more important for data scientists to be aware of privacy concerns, and avoid bias, and misinterpretation. This video includes panelists that all have expertise in the data ethics and regarding public relations. For example, if you publish a...

2021, Bias, Code of Ethics, Education & Training, Legal & Policy, Video

Bias Avoidance, Misinterpretation, Privacy Concerns, Storytelling

Developing an Online Data Ethics Module Informed by an Ecology of Data Perspective

May 4, 2023 by [Inbressa](#)

Author: Xiaofeng Tang, Eduardo Mendieta, Thomas A. Litzinger; Publisher: Science and Engineering Ethics; Publication Year: 2022. The following article discusses how a lack of training in ethical theories and related pedagogy has kept many engineering faculty members from teaching data ethics, an important aspect of engineering research that has become more salient in recent years. This paper describes the development of a module, which includes concepts, cases, policies, and...

Search

Search

Recent Posts


[Panel Discussion: Data Ethics in the Stories We Tell](#)

[Data Science Ethics in 6 Minutes](#)

[Review of Digital Economy Research in China: A Framework Analysis Based on Bibliometrics](#)

[A 20-Year Community Roadmap for Artificial Intelligence Research in the U.S.](#)

[Developing an Online Data Ethics Module Informed by an Ecology of Data Perspective](#)

Institute for
ADVANCED
ANALYTICS
NC STATE UNIVERSITY

Data Ethics Repository ([DER SHEET](#))

- Each week, select TWO resources about data ethics (articles, chapters, books, videos, documentaries, podcasts, laws, regulations, white papers, websites, conferences, lunch-and-learns, microlearning, certifications...
 - Select resources from 2017-2023
 - Focus on practicum industry/field when you know your sponsor
- Write ~75-200 words **explaining why the resources is important/interesting to you and why it would be helpful for other data professionals.**
 - **NOT** a book/article/video review
 - Yes, provide an overview of content, but share why the resource is important
 - You may use AI to CHECK your draft. **Do not use AI to create your response.**
 - **Things are changing daily—so the more recent resources are better**

artificial intelligence,data science

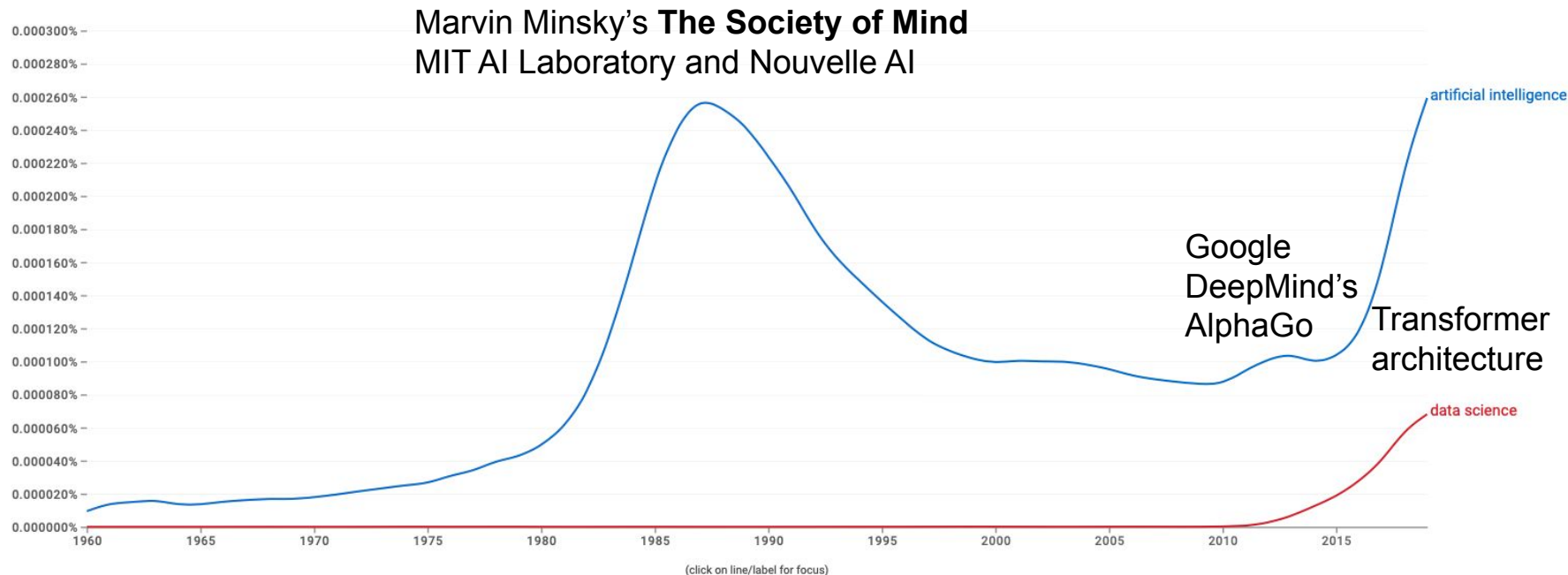


1960 - 2019

English (2019)

Case-Insensitive

Smoothing of 1





● artificial intelligence
Search term

● data science
Search term

+ Add comparison

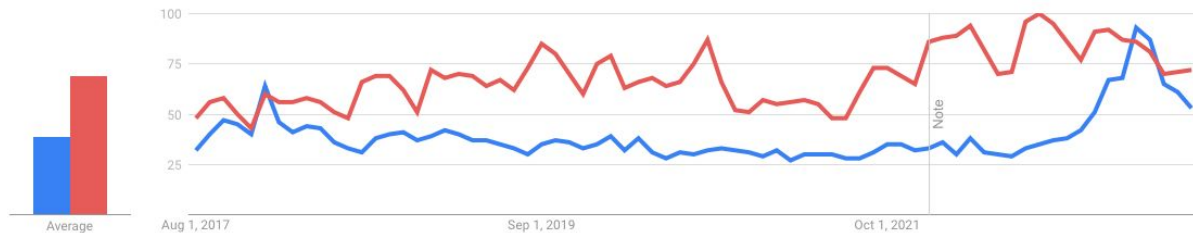
United States ▼

7/22/17 - 8/22/23 ▼

All categories ▼

Web Search ▼

Interest over time ?



Assignments

Individual

- Meet the weekly deadlines for DER and Questions.
- You CAN work ahead.
- Ask if you have questions/concerns/ideas.
- It is **ok** for repeat entries that other students have already selected—ideally, check to see if someone else has already submitted a resource.
 - If it is a duplicate, what can you add that the other person did not?

[Data Ethics Repository Sheet](#)

Assignments

Team

- Create a ONE PAGER that is focused on ethics framework or guidelines for your practicum team
- Create what is going to be most appropriate/useful for your team.
- There is NOT one way to do the one-pager (practice creative and critical thinking)
- You can start on this right away and then refine when you know your sponsor (or after you have met with your sponsor)

Options for Team One-Pager

Team Ethics Framework and Considerations for Practicum Project

Use your [Critical & Creative Thinking](#) Skills

One Page Document/Slide about ethics for your practicum/framework

Lotus Blossom Brainstorming about ethics for your practicum/framework

- <https://www.lucidmeetings.com/glossary/lotus-blossom-technique>
- <https://uxdesign.cc/the-lotus-blossom-method-ideation-on-steroids-100adb26a0c2>

Morphological Matrix about ethics for your practicum/framework

- <https://hatrabbits.com/en/morphological-matrix/>

Concept Map about ethics for your practicum/framework

- [https://www.mural.co/use-case/mind-map?utm_medium=paid-search&utm_source=adwords&utm_campaign=201101-Mind_Maps&utm_adgroup=Templates - Mind Maps&utm_campaign_id=11208697411&utm_content=mind%20map&utm_adgroupid=110300561736&qclid=Cj0KCQjwiIKYBhC6ARIsAGEds-LOE734rkVZ8ZYbdzjOHosEqXtTtiwH29N7xisYKbLheN0yDPbhBQlaAo45EALw_wcB](https://www.mural.co/use-case/mind-map?utm_medium=paid-search&utm_source=adwords&utm_campaign=201101-Mind_Maps&utm_adgroup=Templates%20Mind_Maps&utm_campaign_id=11208697411&utm_content=mind%20map&utm_adgroupid=110300561736&qclid=Cj0KCQjwiIKYBhC6ARIsAGEds-LOE734rkVZ8ZYbdzjOHosEqXtTtiwH29N7xisYKbLheN0yDPbhBQlaAo45EALw_wcB)
- <https://lucidspark.com/blog/what-is-a-concept-map>

Have a different idea? Talk to SEW to get it approved.

Brainstorming	Tutor/Learn something new	Practice for interview	ChatGPT	Bing	Bard	Cheating	Intellectual Property	Bias
Adjust tone/style	Benefits	Review final draft	CoPilot	Tools	Playground	Accessibility	Ethics	Access
Summarize	Create examples	Break writer's block	Wu Dao	Moonbeam	Jasper	Privacy	Transparency	Misuse
AI Bill of Rights	Supreme Court	Congress	Benefits	Tools	Ethics	Magic Phrases	"Let's take this step by step"	Personas
EU AI Act	Regulations	Copyright	Regulations	AI Text Generators	Prompts	Be specific	Prompts	Interact & Refine
NIST: AI Risk Management Framework	GDPR	AI and Data Act	Work	Higher Education	What's Next?	Context	Ask for the process	Stay on topic
Expectations of employers	"AI won't take your job. Another person using AI will take your job."	Productivity	Rethinking assignments	Data literacy	Involve students	Specialized ChatBots	AI integration	Legislation
Coding	Work	Reports	University policies	Higher Education	Classroom policies	Adapting to rapid change	What's Next?	Real time updates
Emails	Review process	Drafts	Incorporating w/in curriculum	Disrupt	Keep informed	The hype vs. reality	Human in the loop	Case Studies

Morphological Matrix for creating a new kind of pet

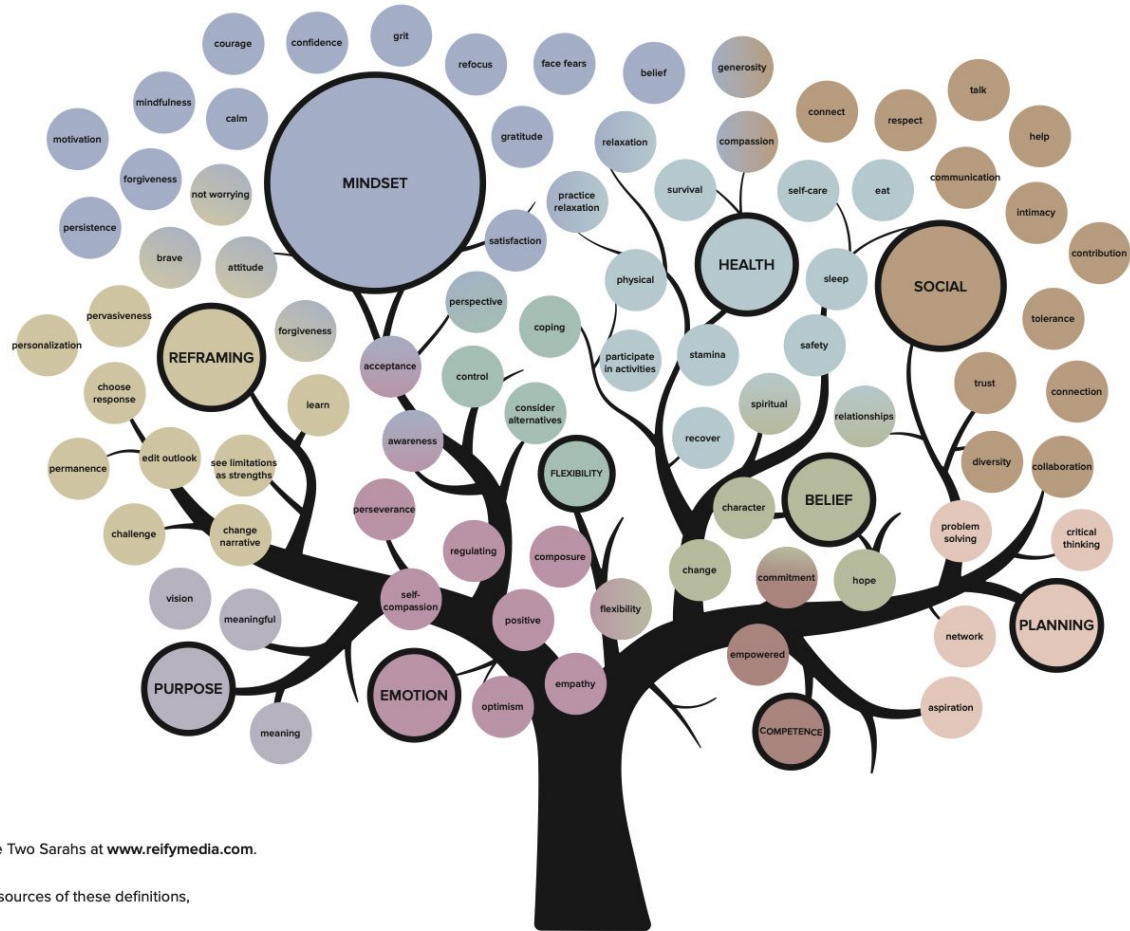
Attribute	SIZE	SKIN	DIET	HABITAT	BEHAVIOR
1	Tiny	Scaly	Herbivore	Salt water	Shy
2	Small	Furry	Carnivore	Fresh water	Friendly
3	Medium	Feathered	Omnivore	Desert	Aggressive
4	Large	Hairless	Cannibal	Forest	Curious
5	Really Big	Slimy	Estivator/ Hibernator	Jungle	Evil

Roll dice or pick random number for each row to generate (sometimes nonsensical) ideas..

5 - 3 - 4 - 1 - 2

The Resilience Tree

When people talk about resilience, these are the descriptions and actions that they discuss.



(c) 2021. Dr. Sarah Egan Warren and Dr. Sarah Glova. Learn more about The Two Sarahs at www.reifymedia.com.

This infographic is based on 18 definitions of resilience. To learn about the sources of these definitions, visit www.reifymedia.com/resiliencetree.

What's Next

- Look at Moodle
 - Submit at least one question for Emily Hadley in **Moodle** before Thursday at 5pm
 - Emily's talk is Friday 1-3pm on Zoom
 - Start working on DER and submit 2 by 8/30
 - Start thinking about One Pager with Practicum Team
-

References

Mühlhoff, R. (2021, July 31) "Predictive privacy: towards an applied ethics of data analytics. *Ethics and Information Technology*, 23, 675–690 (2021).

<https://doi-org.prox.lib.ncsu.edu/10.1007/s10676-021-09606-x>

Patil, D.J., Mason, H., and Loukides, M. (2018, July 25). *Ethics and Data Science*. O'Reilly Media.

Lang, C., Macfadyen, L.P., Slade, S., Prinsloo, P., & Sclater, N. (2018, March 7). The complexities of developing a personal code of ethics for learning analytics practitioners: implications for institutions and the field. *Proceedings of the 8th International Conference on Learning Analytics and Knowledge*, 436-440. <https://doi.org/10.1145/3170358.3170396>

Explore More

[Predictive Policy: towards an applied ethics of data analytics](#)

[The complexities of developing a personal code of ethics for learning analytics practitioners: implications for institutions and the field.](#)

References

Dabas, A. (2020, July 27). "Algorithmic Bias in Real-World: Practical Examples of Bias." *Medium*.

<https://adabhishekdbas.medium.com/algorithmic-bias-in-real-world-b98808e01586>

Martinez, E. & Kirchner, L. (2021, August 25). "The Secret Bias Hidden in Mortgage-Approval Algorithms." *The Markup*.

<https://themarkup.org/denied/2021/08/25/the-secret-bias-hidden-in-mortgage-approval-algorithms>

Gerard, C. (2020, November 17). Bias in machine learning. In *Practical Machine Learning in JavaScript: TensorFlow.js for Web Developers*. (pp 305-316).

Apress. https://doi.org/10.1007/978-1-4842-6418-8_7

van Otterloo, S. (2018, May 11). "Algorithmic bias and how to avoid it in software projects." *ICT Institute*.

<https://ictinstitute.nl/algorithmic-bias-project-management/#:~:text=Algorithmic%20bias%20means%20that%20the,not%20aware%20of%20the%20bias.>

Explore more:

[Algorithmic Bias in the Real World](#)

[The Secret Bias Hidden in Mortgage Approval Algorithms](#)

References

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Explore more:

[The impact of diversity: a review of the evidence](#)

[AI for all: defining the what, why, and how of inclusive AI](#)

[Why AI can't move forward without diversity, equity, and inclusion](#)

[6 Ways UX Researchers can be Advocates for Humans](#)

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Explore More:

[Ethics and Data Science](#), [Data analytics in a privacy-concerned world](#), [6 examples of online privacy violation](#), [GDPR Fines: Biggest GDPR Violation Examples](#), [Predictive privacy: towards an applied ethics of data analytics](#), [10 Big Data Analytics Privacy Problems](#), and [The complexities of developing a personal code of ethics for learning analytics practitioners: implications for institutions and the field](#)

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Explore More:

[Privacy and Analytics - it's a DELICATE issue: A Checklist for Trusted Learning Analytics.](#)



Ethical Considerations for Data Professionals

Dr. Sarah Egan Warren, Class of 2024

CLASS TWO THEME: Emily Hadley



Ethical Considerations for Data Professionals

Dr. Sarah Egan Warren, Class of 2024

CLASS THREE THEME: BIAS



Agenda

- Reflecting on Emily Hadley's Talk
- Alumni Hiwot Tesfaye video
- Types of Bias
 - More in the spring when we do Bias Case Studies
- Looking Ahead



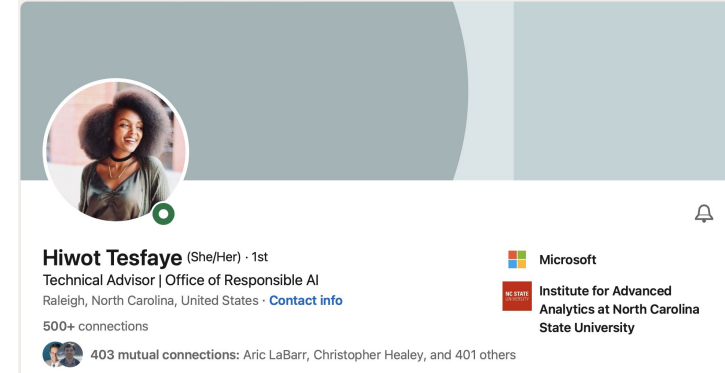
Alumni Voices

Overview of Responsible AI in Practice,
Hiwot Tesfaye
Previously at SAS, now Microsoft
(Technical Advisor | Office of Responsible AI)

- <https://www.youtube.com/watch?v=CbaEC6pH3Cg>

Longer discussion on a podcast

- <https://podcasts.apple.com/us/podcast/analytics-exchange-podcasts-from-sas/id1531716452?i=1000511694194>



Cognitive Bias from Emily Hadley's Talk

- Bias is “deviation from a standard” Danks & London, 2017
 - Algorithmic Bias
 - Statistical Bias
 - Cultural Bias
 - Legal Bias
 - Moral Bias
 - Cognitive Bias

Cognitive Bias

“Cognitive biases are unconscious **errors in thinking** that arise from problems related to memory, attention, and other mental mistakes... These biases result from our **brain’s efforts to simplify** the incredibly complex world in which we live... A cognitive bias is a subconscious error in thinking that leads you to **misinterpret information** from the world around you, and **affects the rationality and accuracy of decisions and judgments.**”

<https://www.simplypsychology.org/cognitive-bias.htm>

*We will discuss explicit/implicit bias in more depth in the spring.

Cognitive Bias Resources

- Cognitive Bias \ Ethics Defined
 - <https://www.youtube.com/watch?v=TIOUnOWfw3M>
- How to Outsmart Your Own Unconscious Bias
 - <https://youtu.be/GP-cqFLS8Q4>
- We All Have Implicit Biases. So What Can We Do About It?
 - <https://www.youtube.com/watch?v=kKHSJHkPeLY>

Bias

Confirmation Bias

- “When the person performing the data analysis wants to prove a **predetermined assumption** and will **intentionally exclude** particular variables from an analysis until it comes to the wanted conclusion.”

Selection Bias or Sample Bias

- “When the sample of data used is **not a good reflection of the population.**”
 - Incomplete or incorrect collection of data

Prejudice Bias

- “Result of **training data that is influenced by cultural or other stereotypes.**”

Bias

Expectation Bias

- Client believes they understand their data and don't readily agree to findings that **contradict or surprise**

Look Ahead Bias

- Past **may not** predict the future

Cognitive Biases

1 Anchoring	Over reliant on 1st piece of info	11 Overconfidence	Take greater risk because of belief
2 Availability Heuristic	Overestimate the importance of info available (anecdote)	12 Placebo Effect	Believing in certain effect
3 Bandwagon Effect	Groupthink	13 Pro-Innovation	Overvalue usefulness / undervalue limitations
4 Blind-spot	Fail to recognize bias in yourself	14 Recency	Latest information is more important than older data
5 Choice-supportive	Feel more positive about your choice even if flawed	15 Salience	Focus on most easily recognizable/notable information
6 Clustering Illusion	Seeing patterns in random events	16 Selective Perception	Expectations influence perception, focus on interests, ignore uninteresting
7 Conservatism	Favor prior evidence over new	17 Stereotyping	Expecting certain qualities
8 Information	Seeking more info with no effect on decision ALSO measurement error	18 Survivorship (type of sample selection bias)	Misjudge because only looking at success
9 Ostrich Effect	Ignore dangerous/negative info	19 Zero Risk	Certainty over any risk
10 Outcome	Judging on outcome rather than HOW decision was made		

Activity

In your homework teams

- Sketch your term/explain your term (be sure to put your term on the page)
- Include how the term is relevant to data science
- Show how you can check for or alleviate the bias

Select one person to report out.

Talk through at Document Camera.

All 19 will be shared during next ECDP class.

Looking Ahead

Continue adding entries to [DER](#)

- Please use a 1 and not an X in the columns F-R as shown in example
 - Go back and fix if you used X
- Working ahead is great!
- If you want to share beyond your required entries, add to the “Met the requirements, but found something to add?” tab (this is an ongoing project and will stretch beyond Fall 1)

Work on One Pager with Practicum Team

For ECDP Class 4, **be prepared to teach your practicum team about your favorite resource so far**. Not a formal presentation. Discuss takeaways, reflect on how it is important/interesting to you, and highlight how it is important to the field of analytics.



Ethical Considerations for Data Professionals

Dr. Sarah Egan Warren, Class of 2024

CLASS FOUR THEME: Take Aways



Agenda

- Cognitive Bias Sketches ([ADD LINK!](#))
- DER Review
- Alumni Video
- Sharing with Practicum Team
- Best of the Best
- Looking Ahead

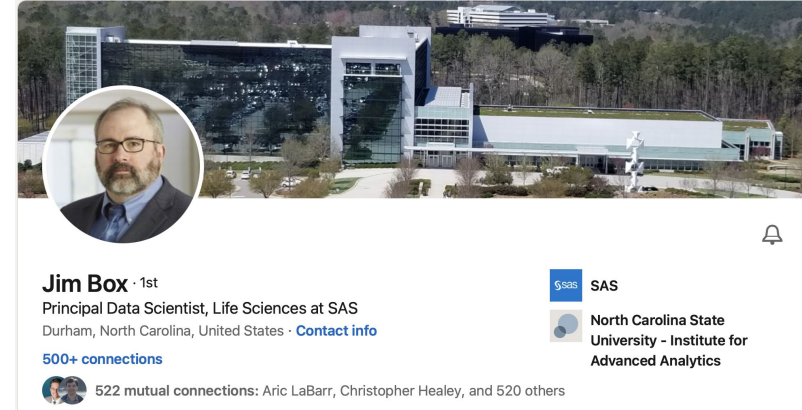


Alumni Voices

Jim Box

Principal Data Scientist, Healthcare &
Life Sciences at SAS

- [Jim Box video excerpt](#) 12:18-20:54





Sharing

- Share out the most important information from your resource to your practicum team
- Discuss take aways
- Reflect on how it is important/interesting to you
- Highlight how it is important to the field of data analytics
- Take turns (~2-3 minutes per person)
- Select **best/most interesting resource** to share with the whole group

25 minutes



Best of the Best

- Share the name of the resources
- Reflect on how it is important/interesting to you
- Highlight how it is important to the field of data analytics
- 1-2 minutes

Looking Ahead

- Continue adding entries to [DER](#)
- Submit question for Patrick Hall
- Work on Practicum Team One Pager (due September 27)



Ethical Considerations for Data Professionals

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CLASS FIVE THEME: Patrick Hall