

Making Ethical Decisions Is Hard!

Stephanie Shipp, Donna Lalonde, and Wendy Martinez

Introduction

It is hard to make ethical decisions.

Your first reaction to reading this statement may be a surprise, but our experience as practitioners and educators has taught us that it *is* difficult and requires practice and tools.

In the early years of the “big data revolution,” big data was described by four or five v’s (or more): volume, velocity, variety, veracity, and value. Although intended to describe data, the five v’s can provide insights into what makes ethical decision making hard. The volume of work, expectation of speed, variety of problems, veracity, or—maybe more explicitly—provenance of the data, and value of the work, viewed from the diverse and sometimes competing perspectives of stakeholders, can make it challenging to navigate the data science landscape ethically.

As the field grows, the need for resources and tools has become more urgent. This article briefly examines the history of several ethical guidelines and frameworks and describes how the Academic Data Science Alliance’s (ADSA) Data Science Ethos (<https://ethos.academicdatasience.org/>) and the ASA’s Ethical Guidelines for Statistical Practice (<https://www.amstat.org/your-career/ethical-guidelines-for-statistical-practice>) can support ethical decision-making at different stages of the data science life cycle.

The Belmont Report, which was created by the National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, described another set of ethical principles. The report responded to the commission’s

charge “to identify the basic ethical principles that should underlie the conduct of biomedical and behavioral research involving human subjects and to develop guidelines which should be followed to assure that such research is conducted in accordance with those principles.”

In an interview celebrating the 25th anniversary of the report’s publication, one of the commissioners said, “If I could go back and do it over again, would I do some things differently? Probably. Though I think what we did at the time was good for its time. Would I add principles? I don’t know if I would add principles so much as I would try to spell out better than we did the inner meaning of the three principles that we had.”

This reflection reinforces the need for continued work to ensure practitioners, educators, and students are prepared to grapple with and resolve the challenges associated with the practice of ethical data science (<https://www.hhs.gov/ohrp/education-and-outreach/luminaries-lecture-series/belmont-report-25th-anniversary-interview-klebacqz/index.html>).

In the age of data science and as practitioners, researchers, and students, it seems reasonable to ask, “What are the basic ethical principles that should underlie the conduct of data science?” At the foundation is the concept of *ethos*, which is described as the spirit or character of the professional community.

The ADSA Data Science Ethos uses the idea of *lenses*, which are structured ways of thinking about

the social and ethical contexts relevant to each stage of the data science research and development process. This focus highlights the responsibility of practitioners to consider the impact of their work.

The ASA Ethical Guidelines for Statistical Practitioners acknowledge that statistical practitioners are members of many professional communities, so ethical practice may require balancing competing interests. As data science practitioners and educators, we must be intentional and conduct data science research and practice ethically.

History

Ensuring the ethical conduct of research has a rich history that can be examined from the perspective of data science ethics. The Nuremberg Code (Shuster. 1997) was created in 1947 after the notorious World War II experiments involving people. This written document established 10 ethical principles for protecting human subjects and foreshadowed the Belmont Commission. The Belmont Commission was convened in the late 1970s, almost 30 years later—after the moral failures of researchers became known.

A famous example of these failures is the Tuskegee Syphilis Study, conducted from 1932–1972 to observe the natural progression of untreated syphilis in poor African American men. None of the men were told that they had the disease and none were treated with penicillin, even after the antibiotic was proven to treat syphilis successfully.

The Belmont Commission issued three principles for the conduct of ethical research:

- **Respect for people**—treating people as autonomous and honoring their wishes
- **Beneficence**—understanding the risks and benefits of the study and weighing the balance between (1) doing no harm and (2) maximizing possible benefits and minimizing possible harms
- **Justice**—deciding if the risks and benefits of research are distributed fairly

These principles are now called the Common Rule and govern federally funded research. The Belmont Commission provided the foundation for Institutional Review Board (IRB) principles and focused on research involving human subjects in experiments and studies. To be eligible for federal grants and contracts, an IRB approval is required, but many institutions also require IRB review for research conducted by faculty, students, and all those under the university's purview.

Some universities, such as the University of Virginia, have their own IRBs for social and behavioral research and another for health sciences research. There are also independent organizations (e.g., <https://www.wcgclinical.com/solutions/irb-review/>) that provide services to agencies or other entities.

The Responsible Conduct of Research training program (<https://www.niaid.nih.gov/research/responsible-conduct-research-training>) grew from efforts to implement the Belmont principles. The National Institute of Health and National Science Foundation requires undergraduate and graduate students to learn about the complex methodological, ethical, and regulatory challenges they might

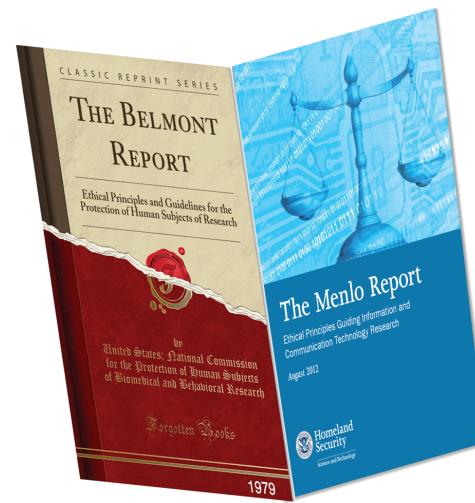
face when conducting research. The training aims to promote research integrity, protect humans and animals, and maintain trust in the research enterprise. Other disciplines, such as computer scientists and engineers, have not been trained in these principles, but that is changing.

In 2012, the Department of Homeland Security created a Menlo Commission to bring the Belmont principles to the information communications and technology (ICT) world. The Menlo Report (and its companion report, "Applying Ethical Principles") expanded the Belmont principles in two critical ways. They added a fourth principle—Respect for Law and Public Interest—that extends the principle of beneficence to include all relevant stakeholders. It expands the focus to include "research with human-harming potential," not just a focus on "research on human subjects."

This change is important in the data science age, where using technologies and repurposing data can expose people to risks and harm. The Menlo Report extended the Common Rule by focusing on benefits to society in the digital age, not just the human subjects who are part of a study.

The Menlo Report also described why a broader view of ethics is needed. Data science has evolved as a result of the digital age that allows for access to and repurposing of massive amounts of administrative and opportunity data. This environment has changed the ethics landscape in the following ways:

- **Scale**—Massive data sets are now available that can be integrated and used in analysis to improve the understanding of society.
- **Speed**—Increased efficiency of IT systems means results affecting millions of people can be produced quickly.



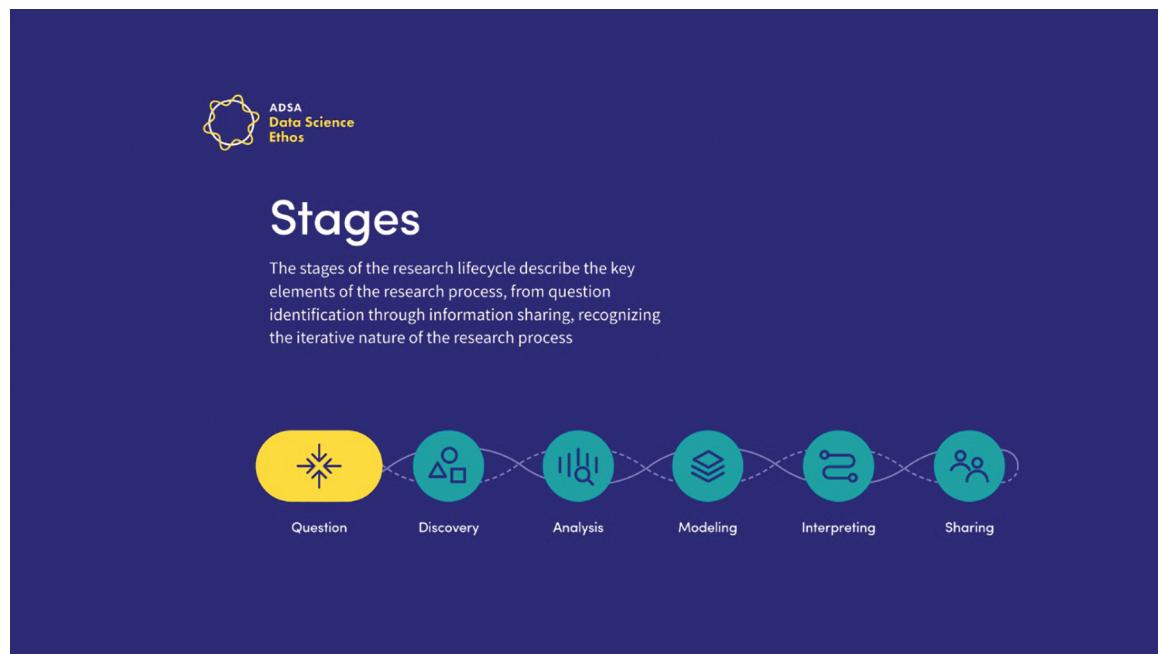
Resources for ethical data work.

- **Tight coupling of ICT resources, interconnected via networks**—Smartphones can contain a vast array of sensitive yet rich data for analysis.

Data science in this digital age can also have a negative impact on research activities that depend on cooperation, such as obtaining informed consent and mitigating actual harm. This is because the data are decentralized, widely distributed, and opaque in that data users are not privy to the inner workings of applications, devices, and networks. This creates an increased need for ethical guidelines and tools to help data scientists conduct their research with an ethical lens.

Data Science Ethos Underpinning—Science Technology Studies

To begin, some background about the discipline of Science Technology Studies (STS) provided the theoretical foundations for the Data Science Ethos. The National Science Foundation (NSF) defines STS as "an interdisciplinary field that investigates the conceptual foundations, historical developments and social



Research Lifecycle Stages: Questions, (Data) Discovery, Analysis, Modeling, Interpreting, and Sharing.

contexts of science, technology, engineering, and mathematics (STEM), including medical science.”

Professional associations in the natural sciences, technology, social sciences, and humanities support the interdisciplinary field. The Society for Social Studies of Science (4S) (<https://4sonline.org/>), which was founded in 1975, reflects the interdisciplinary field by bringing together scholars from many fields who are interested in the “interaction of science, technology, or medicine and society.”

According to the STS Wiki (<https://stswiki.org>), the underpinnings of the field are “how social, political, and cultural values affect scientific research and technological innovation; and how scientific research and technological innovation affect society, politics, and culture.”

Having begun in the 1960s, this interdisciplinary field now offers undergraduate and graduate degrees in existing disciplines. The Cornell

University Department of Science & Technology Studies (<https://sts.cornell.edu/>) describes the “thread connecting these diverse issues” as the desire to study science and technology as “inherently social activities.” The University of Virginia’s Science and Technology program (<https://engineering.virginia.edu/node/9551>) is located within the School of Engineering and Applied Science. The program aims to help undergraduates “understand the relationships between technology and society; are equipped to be ethical engineers; and have strong proficiency in written communication.”

These two examples provide additional context for the areas of knowledge considered by this field.

Data Science Ethos

The vision of the Data Science Ethos was to view the research and development life cycle through multiple lenses, thus ensuring

that the impact of data science on society was central to decision-making throughout the processes.

The Data Science Ethos introduction states: “We see a need for a data science framework that includes explicit societal contexts and makes questions of social good actionable. The result will be a more true-to-life model of the data science life cycle that shows how societal questions are a constitutive part of the day-to-day work of a data scientist.”

This is accomplished by viewing the data science life cycle stages through the four lenses of: Positionality, Sociotechnical Systems, Power, and Narratives.

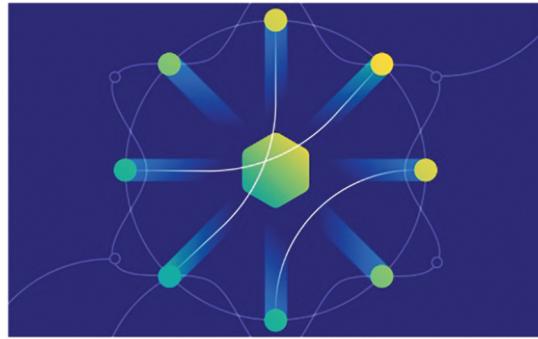
The Data Science Ethos describes the life cycle stages as developing an investigative question, data discovery, exploratory data analysis, modeling, interpreting, and sharing. The four lenses are applied at each stage. The process is iterative, so work in one stage may result in revisiting a preceding stage. The Ethos



Positionality

Diversity of human experience

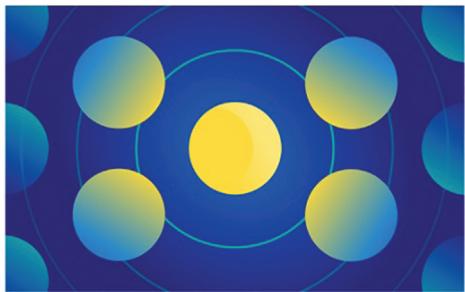
A person's capacity to consider how opportunities and limits of their identity, expertise, or personal situation are **shaped by their environments** and inform their perspectives and actions.



Sociotechnical Systems

Technology interacting with society

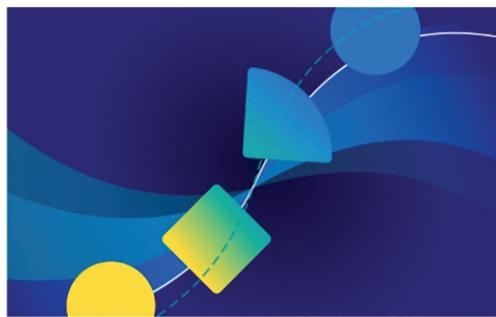
The reciprocal **influences between technical systems and individuals** who design, develop, and operationalize them; the hybrid nature of organizations in which individuals and technological actions are constantly interacting with one another.



Power

Asymmetries in agency

A person or technology's **asymmetric capacity to structure or alter others' behavior**. Scientific and technological powers are always intertwined with political and socioeconomic power.



Narratives

Dominant discourse

How we **talk about how the world works** and what futures are worth pursuing. In science, researchers develop an argument (a claim) supported by pieces of evidence (data) collected in their field world.

The four lenses of the Ethos in action.

helps the practitioner understand how to use the lenses by providing examples of questions that could be asked to help guide the work.

For example, at the questioning stage, one might ask, "What is the dominant narrative in which the

research question is embedded?" This question will help the researcher or practitioner use the Narratives lens to guide the project.

Additional questions help the researcher go deeper. For example, as follow-up, one might ask: "Are there

alternative narratives you could consider? Does your research question include a social justice or public good component? Why or why not?"

Another example is the Sociotechnical Systems lens applied to the modeling stage. The Data

Science Ethos considers the modeling stage, in part, as the use of analytical tools. One question that helps the researcher or practitioner use the Sociotechnical Systems lens is, “What biases might be built into these tools and the data set(s) they have been trained on?”

For more examples, spend time on the Data Science Ethos website (<https://ethos.academicdatascience.org>) to work through the case studies and understand how the lenses can be applied to each stage.

ASA Guidelines

The ASA Ethical Guidelines for Statistical Practice reflect the efforts of many individuals. Writing and reviewing the guidelines is the responsibility of the ASA Committee on Professional Ethics (CoPE). The committee reviews and updates the guidelines every five years.

The revision process requires many months of effort and includes requests for comments from the broader community. The ASA Board of Directors approved the most recent revisions in February 2022. The guidelines aim “to help statistical practitioners make decisions ethically.”

The guidelines define statistical practice as including activities such as designing the collection of, summarizing, processing, analyzing, interpreting, or presenting data, in addition to developing and deploying models or algorithms. This definition of statistical practice clarifies how the guidelines can and should be applied to the data science life cycle.

The guidelines have eight overarching principles, each more fully developed by explicit statements of expected behavior. For example, Principle A is Professional Integrity and Accountability, which requires taking responsibility for one’s work. Principle A specifies

12 desired behaviors; for example, “Uses methodology and data that are valid, relevant, and appropriate, without favoritism or prejudice, and in a manner intended to produce valid, interpretable, and reproducible results.”

The guidelines also have an appendix, Responsibilities of Organizations/Institutions, which guides organizations and institutions to ensure a culture of ethical statistical practice exists.

Bringing It Together Through Case Studies

The Data Science Ethos and the ASA Ethical Guidelines complement each other. Both operationalize practitioners’ ethical responsibilities. The Guidelines help statistics practitioners make decisions ethically, while the Ethos “offers practitioners structured ways of thinking about the social and ethical contexts relevant to each stage of the data science research process.”

Three overarching ASA principles are the most relevant for adding an ethical practice framework to the Data Science Ethos:

Principle A—Professional Integrity and Accountability,

Principle B—Integrity of Data and Methods

Principle C—Responsibilities to Stakeholders

The complete guidelines and related resources made available by the ASA Committee on Professional Ethics can be found at <https://community.amstat.org/ethics/home>.

To make these ideas real and concrete, the Data Science Ethos website includes three case studies. A table comparing the Data Science Ethos lenses and the American Statistical Association’s Ethical Guidelines for Statistical Practice (Principles A, B, C) is provided.

The Guidelines can be used to explore the Data Science Ethos case study, which examines how property taxes were assessed in two major metropolitan areas to determine whether people were paying a disproportionate share.

The “Paying Your Share Case Study” is based on an investigative journalism project published by ProPublica and the *Chicago Tribune* in December 2017. Sandhya Kambhampati and Jason Grotto investigated industrial and corporate property assessments in Cook County and Chicago for the ProPublica project. The work was made available in a public GitHub repository to provide documentation of the methods and code used to write the articles.

In collaboration with Caleb Melby, Grotto continued the project with an investigation of practices of the New York City (NYC) Finance Administration. The NYC project resulted in the publication of a Bloomberg article. These two investigations form the basis of the case study.

Using the lenses and the ASA Ethical Guidelines for Professional Practice, the data science practitioner and students can have an authentic experience of ethical decision-making. The following discussion shows how the Ethos and the ASA Guidelines can inform ethical practice.

The ASA Guidelines state that “all those who engage in statistical practice, regardless of job title, profession, level, or field of degree,” are accountable to stakeholders and responsible for ethical practice. The data journalists were statistical practitioners in the investigation and reporting of the projects presented in the case study.

Positionality is framed with these questions: “What knowledge and skills did the journalists bring to the definition of the research

question? Are there any missing pieces?” “What are the main ethical challenges of this data investigation?”

Principle A: Professional Integrity and Accountability requires the practitioner to use “methodology and data that are valid, relevant, and appropriate, without favoritism or prejudice, and in a manner intended to produce valid, interpretable, and reproducible results.” By making their analysis public, the journalists were transparent and acted in a manner that is consistent with the guidelines that acknowledge the framing questions.

In the NYC investigation, Preston Niblack, as a public official and economist, is a statistical practitioner and thus has a professional responsibility to follow the Guidelines for Ethical Statistical Practice. He was responsible for using “methodology and data that are valid, relevant, and appropriate, without favoritism or prejudice, and in a manner intended to produce valid, interpretable, and reproducible results.”

In the case study, he is quoted as stating, “To the extent that anybody can understand the process, it was all clearly described in what was provided, but again I am happy to walk you through it. It is not a straightforward process; I will explain how it works as best as I can.”

When viewed through the lenses and the guidelines, this response is unsatisfactory. By comparison, Rob Ross, who became the chief data officer for the Chicago investigation, established a GitHub open data repository to make statistical practices and results transparent. Niblack used the shield of proprietary software.

Principle B: Integrity of Data Methods requires the statistical practitioner to “communicate data sources and fitness for use, including data generation and collection processes and known biases.” The **Sociotechnical** lens asks, “Could

OTHER GUIDELINES AND FRAMEWORKS

ASA Ethical Guidelines for Statistical Practice

<https://www.amstat.org/your-career/ethical-guidelines-for-statistical-practice>

United Kingdom Framework

<https://www.gov.uk/government/publications/data-ethics-framework>

United Nations Data Strategy

https://www.un.org/en/content/datastrategy/images/pdf/UN_SG_Data-Strategy.pdf

United States Data Ethics Framework

<https://resources.data.gov/assets/documents/fds-data-ethics-framework.pdf>

What is Data Ethics?

<https://royalsocietypublishing.org/doi/10.1098/rsta.2016.0360>

these systems be biased, and if so, how?”

Although Niblack was responsible to all the stakeholders, including the software vendor, presenting severely redacted material was inconsistent with the guidelines and made it impossible to address the sociotechnical questions. In contrast, the data journalists used Jupyter Notebooks, which is open to all. This demonstrated an awareness of the requirements of Principle B.

In **Principle C: Responsibilities to Stakeholders**, the guidelines state, “Strives to make new methodological knowledge widely available to provide benefits to society at large. Presents relevant findings, when possible, to advance public knowledge.” The **Power** lens asks, “Who are the main, visible, and apparent stakeholders in this data investigation? Are there individuals or groups who could be considered stakeholders and who are not represented?”

The open data hub created as a result of the Chicago research project is a concrete example of how stakeholder interests can be addressed and effectively applying the guidelines.

These examples are not meant to be comprehensive, but show how using the Ethos lenses with the ASA Ethical Guidelines can help practitioners and students accomplish the hard work of ethical decision-making.

Moving Forward

As acknowledged in the introduction, ethical decision-making is hard and requires practice. The case study approach can be an effective way to raise awareness and operationalize data science frameworks and guidelines.

The Data Science Ethos currently provides two additional case studies and a “how it works” guide. One case study is about estimating the population with cellphone records. The other is a citizen

Table 1—Bringing It All Together—Alignment of the Data Science Ethos and ASA Ethical Guidelines (adapted from Data Science Ethos)

Data Science Ethos Lenses https://ethos.academicdatasience.org/	ASA Ethical Guidelines for Statistical Practice https://www.amstat.org/your-career/ethical-guidelines-for-statistical-practice
<p>Positionality</p> <p>Assumptions and bias</p> <ul style="list-style-type: none"> • What assumptions do you bring to work based on your professional <i>and</i> personal experience and your experiences with culture, gender, class, and race? • How might those assumptions influence the questions you ask and the answers you find? <p>Role and expertise</p> <ul style="list-style-type: none"> • Why are you the appropriate person to approach and develop this research question? • What are the opportunities and limits of your expertise? • What other kinds of expertise would you need? • Who are the other persons involved in your project, and how are you connected to them? • What missing expertise do you think they bring to the project? <p>Stakeholders, providers, and beneficiaries</p> <ul style="list-style-type: none"> • Whom do you need to rely on to make this project happen? • Who will benefit from your work? • Who are the relevant stakeholders that you/your team needs to partner with to understand the research question from another perspective? • How are stakeholders, providers, and beneficiaries interconnected? <p>Sociotechnical systems</p> <p>Ways to reflect on sociotechnical systems</p> <ul style="list-style-type: none"> • How would you describe the sociotechnical system your work is embedded in? • How would you describe the sociotechnical system your work has an impact on? • How are these two systems related? • What social constructs or assumptions are inherent in your data set and presented as fact? • What actions (and whose actions) are enabled by data science tools, and what steps are proscribed or hindered by them? • How does your data science project seek to contribute to modifying an existing sociotechnical system? <p>Describe the tools and technologies implemented in your research process</p> <ul style="list-style-type: none"> • In which phase of the process are they deployed? What are their roles? How do they interact with one another? • What are the risk-benefit arguments for using (or not using) these technologies and or tools? • Who or what is held responsible when something goes wrong? 	<p>Principle A. Professional Integrity and Accountability</p> <p>A1. Takes responsibility for evaluating potential tasks, assessing whether they have (or can attain) sufficient competence to execute each task and that the work and timeline are feasible. Does not solicit or deliver work for which they are not qualified or that they would not be willing to have peer reviewed.</p> <p>A2. Uses methodology and data that are valid, relevant, and appropriate, without favoritism or prejudice, and in a manner intended to produce valid, interpretable, and reproducible results.</p> <p>A3. Does not knowingly conduct statistical practices that exploit vulnerable populations or create or perpetuate unfair outcomes.</p> <p>A6. Strives to follow, and encourages all collaborators to follow, an established protocol for authorship. Advocates for recognition commensurate with each person's contribution to the work. Recognizes that inclusion as an author does imply, while acknowledgement may imply, endorsement of the work.</p> <p>A8. Promotes the dignity and fair treatment of all people. Neither engages in nor condones discrimination based on personal characteristics. Respects personal boundaries in interactions and avoids harassment, including sexual harassment, bullying, and other abuses of power or authority.</p> <p>Principle C. Responsibilities to Stakeholders</p> <p>C2. Regardless of personal or institutional interests or external pressures, does not use statistical practices to mislead any stakeholder.</p> <p>C4. Informs stakeholders of the potential limitations on use and reuse of statistical practices in different contexts and offers guidance and alternatives, where appropriate, about scope, cost, and precision considerations that affect the utility of the statistical practice.</p> <p>C6. Strives to make new methodological knowledge widely available to provide benefits to society at large. Presents relevant findings, when possible, to advance public knowledge.</p> <p>C8. Prioritizes both scientific integrity and the principles outlined in these guidelines when interests are in conflict.</p>

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<p>Power</p> <p>Power dynamics in the project</p> <ul style="list-style-type: none"> Who influences the research and who does not, even while it affects them? Who gets to decide if the work is valid or sound, and who may dispute that conclusion? Whose power is increased through the work, and whose power is diminished? Through what mechanisms, methods, or technologies is that power wielded? <p>Power dynamics of the project</p> <ul style="list-style-type: none"> What are the assumptions about power in your project? Who has it? Who needs it? How does this landscape impact the definition and execution of the research proposal? Input-output: What kind of power (as input) does your project require? What kind of power (as by-product and output) does your project produce? Transformations: How does the transformed field of power reorient identities, relationships, and life chances? How does the project impact the status quo regarding: <ul style="list-style-type: none"> Power distribution? Power dynamics? To whom has power been given? Was power taken away from someone? Who or what has gained agency? With whom, or what, has the delegation of agency been negotiated? From whom, or what, has the agency been removed? 	<p>Principle A. Professional Integrity and Accountability</p> <p>A3. Does not knowingly conduct statistical practices that exploit vulnerable populations or create or perpetuate unfair outcomes.</p> <p>A9. Takes appropriate action when aware of deviations from these guidelines by others.</p> <p>Principle B. Integrity of Data and Methods</p> <p>B2. Is transparent about assumptions made in the execution and interpretation of statistical practices, including methods used, limitations, possible sources of error, and algorithmic biases. Conveys results or applications of statistical practices in ways that are honest and meaningful.</p> <p>B5. Strives to make new methodological knowledge widely available to provide benefits to society at large. Presents relevant findings, when possible, to advance public knowledge.</p> <p>C4. Informs stakeholders of the potential limitations on use and reuse of statistical practices in different contexts and offers guidance and alternatives, where appropriate, about scope, cost, and precision considerations that affect the utility of the statistical practice.</p>
<p>Narratives</p> <p>Ways to reflect on narratives</p> <ul style="list-style-type: none"> What narratives motivated and informed the creation of this data? What underlying beliefs indicate that data science approaches are appropriate for the question or problem? What kind of change is the work implicitly or explicitly intended to bring about? What narrative is the result of your data science work contributing to? Who do you anticipate will agree with this narrative? Who will have questions about it? Who will resist it? Why is the data you have produced the most interesting to answer your research question? What other alternatives might exist? 	<p>Principle A. Professional Integrity and Accountability</p> <p>A1. Takes responsibility for evaluating potential tasks, assessing whether they have (or can attain) sufficient competence to execute each task and that the work and timeline are feasible. Does not solicit or deliver work for which they are not qualified or that they would not be willing to have peer reviewed.</p> <p>A3. Does not knowingly conduct statistical practices that exploit vulnerable populations or create or perpetuate unfair outcomes.</p> <p>A4. Opposes efforts to predetermine or influence the results of statistical practices and resists pressure to selectively interpret data.</p> <p>Principle B. Integrity of Data and Methods</p> <p>B1. Communicates data sources and fitness for use, including data generation and collection processes and known biases. Discloses and manages any conflicts of interest relating to the data sources. Communicates data processing and transformation procedures, including missing data handling.</p> <p>B2. Is transparent about assumptions made in the execution and interpretation of statistical practices, including methods used, limitations, possible sources of error, and algorithmic biases. Conveys results or applications of statistical practices in ways that are honest and meaningful.</p> <p>Principle C. Responsibilities to Stakeholders</p> <p>C4. Informs stakeholders of the potential limitations on use and reuse of statistical practices in different contexts and offers guidance and alternatives, where appropriate, about scope, cost, and precision considerations that affect the utility of the statistical practice.</p>

science project titled “Crowd the Tap: People Protecting Our Tap Water.” This describes “the first U.S. Environmental Protection Agency (EPA)-funded project that promotes access to safe drinking water by empowering individuals and groups to investigate the piping infrastructure that delivers drinking water to their homes.” Going through the case studies provides the opportunity to see the Ethos (life cycle and lenses) applied to real-world situations.

The Data Science Ethos team is working to add more case studies to support the data science community. *CHANCE* readers are invited to consider creating and adding their own case studies that use the Data Science Ethos, possibly in combination with other frameworks

and guidelines, and sharing them with ADSA.

To get things started, a colleague offered some suggestions for future case studies. Topics suggested for exploration include:

- Describe government statistical agencies and other institutions that have a mission to produce, disseminate, and facilitate the responsible use of statistical information on a public good/public stewardship basis.
- Portray statisticians working in settings that have high societal, very time-dependent impact, and address empirical phenomena that are highly dynamic and uncertain, or statisticians seeking to improve institutions that have deep-seated challenges.

“If an unexpected ethical challenge arises, the ethical practitioner seeks guidance, not exceptions, in the guidelines,” which is how the ASA Guidelines acknowledge that in the complex data science milieu, ethical decision-making requires more than a set of rules. Part of the challenge is simply situating a specific data ethical challenge in the larger space. The ADSA Ethos and the ASA Ethical Guidelines are tools that help navigate this complicated landscape.

We end where we began: *Making ethical decisions is hard*—but our spirit of community, or ethos, will keep us moving forward. □

Further Reading

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Wendy Martinez is the senior mathematical statistician for data science in the U.S. Census Bureau Research and Methodology Directorate. Previously, she served as director of the Bureau of Labor Statistics Mathematical Statistics Research Center and worked in several research positions throughout the Department of Defense. Her research interests include computational statistics, exploratory data analysis, text analysis, and data visualization.

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