Ethics in Data Science Education

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Abstract

There is a growing recognition of the importance of ethics education in data science programs. Recent news stories about data breaches and algorithmic biases indicate that big data projects raise ethical concerns with the potential to inflict harm on a wide societal or global scale. In this paper, we address three main research questions: (1) what curricular recommendations have been proposed for the teaching of ethics in undergraduate data science courses, (2) what codes of ethics are relevant to data science, and (3) how can we characterize the proposed codes to help an educator choose which to include in a data science course? We conclude with an overview of an approach to teaching ethics in undergraduate data science courses.

1. Introduction

The teaching of engineering and technical ethics in undergraduate curriculum is a long-standing practice and a mature field of study. ABET requires students of accredited programs to achieve ethical competencies such as recognizing ethical responsibilities in their profession and making informed decisions. Currently, there is no such standard criteria for students in data science programs. There are, however, multiple reports recommending curricular content for data science programs. In Section 2 of this paper, we examine the role of ethics in these reports.

Data science curricula in practice typically comprise of studies in multiple areas such as mathematics, statistics, machine learning, programming, and data modeling and management. Professional societies representing these areas have codes of ethics for their practitioners, and there are also newly proposed codes specifically aimed at data scientists. In Section 3, we examine codes proposed for data science as well as codes of ethics in foundational fields such as statistics and computer science, as proposed by the American Statistical Association and the Association for Computing Machinery, respectively. We investigate ways to characterize the selected codes to help facilitate a choice of codes by an educator to include in his or her courses.

We conclude with a brief discussion of our ongoing research and an approach to teaching and assessing student outcomes in data science ethics.

2. The Role of Ethics in Curriculum Reports

In this section, we review reports with curriculum recommendations for data science, focusing on their coverage of teaching ethics. The reports are authored by multi-disciplinary teams under the auspices of one or more professional, education-oriented organizations. The focus is on undergraduate data science, but pre-college and graduate studies are also considered. The main focus of the reports is summarized along with a discussion of the role of ethics in each.

2.1 National Science Foundation (NSF)

The US National Science Foundation report on “Realizing the Potential of Data Science” [1] defines a data lifecycle for data science research projects. Ethics permeates every phase of the life cycle, from acquisition, cleaning, using/reusing, and publishing, to preserving/destroying data. A definition of ethics is proposed as determining “proper or improper actions with data in each stage.” [1, p. 8]

The report issues recommendations for a national agenda in 4 topic areas: research, education and training, infrastructure to support data science, and new data driven-scenarios. Ethical considerations are raised in each of these categories. The data science research agenda identifies opportunities to explore research questions across the data life cycle as well as to integrate research across disciplines. The education and training agenda states that “ethics is also becoming a ‘must-have’ in any responsible curriculum.” [1, p. 13] The proposed agenda for education and training recognizes that data exists in a complex environment that includes protecting human subjects in data and performing ethical analysis. The agenda for infrastructure to support data science research and education includes management and accessibility of useful datasets. The goal of the new scenarios is to cope with technical and social challenges “that will render data-driven systems useful, effective, and productive, rather than intrusive, limiting, and destructive.” [1, p. 20] Specifically, in the IoT domain, the report mentions the need for developing “artificial ethics systems” [1, p. 21] for decisions made autonomously by machines.

The ethical topics raised in the report can be summarized in three categories:

1. data management: privacy, bias in data and its usage, sustainable data stewardship, and protection of human subjects,
2. educational training: performing ethical analysis, and
3. application areas: ethics in autonomous systems.

2.2 Park City Math Institute (PCMI)

A report by the Park City Math Institute entitled “Curriculum Guidelines for Undergraduate Programs in Data Science” [2] focuses on technical competencies in subject areas at the curricular level, primarily in mathematics, statistics, and computer science. Ten core courses for an undergraduate data science major are recommended. Ethics is mentioned as a related area of study along with communication and reproducibility. Topics for ethical training include data ownership security, privacy concerns for data analysis, and transparency/reproducibility. Several of the core courses include a mention of ethics: (1) introduction to data science I and II; (2) data curation, management, and organization (e.g., bias in sources of data, security related to authorization and access); and (3) capstone topics include “code that is reproducible and ethical” [2, p. 23]. The specifics of what is meant by “code that is ... ethical” is not explained, other than avoiding plagiarism [2, p. 18], nor are any of the topics for ethical study described beyond a cursory mention.

The ethical topics raised in the report can be summarized in three categories:

1. data management: privacy and security/stewardship,
2. analysis: transparency and reproducibility, and
3. software development: avoiding plagiarism.

2.3 International Data Science in Schools Project (IDSSP)

The curriculum proposed by the International Data Science in Schools Project (IDSSP) is intended for deployment in high schools rather than undergraduate programs, but is included here because it contains the most detailed curricular specifications of the examined proposals; it integrates ethics into the learning modules on technical material rather than treating it as a stand-alone study.

A draft report for two high school data science courses has been released by the International Data Science in Schools Project [3]. The courses are intended to be year-long courses at a pre-calculus level to be taken in the final years of high school. In the IDSSP's “Abbreviated Topic Lists” report, it is notable that ethical discussions accompany technical topics. For example, many topics include a discussion of strengths and weaknesses of the approach. Table 1 highlights excerpts from the Unit 1 and Unit 2 courses that touch on ethical topics.

Table 1. IDSSP Units 1 and 2 Potential Ethics Topics

IDSSP unit/topic area	IDSSP item/ethical issue
1.1 data science and me	1.1 role of data in decision-making (various contexts, e.g., home, business, sport)
	1.3 data science success stories
	1.4 data science disasters
	2.5, 3.4 privacy, security, and openness/accessibility
	4.2-4.5 social/personal consequences; how can prediction and causality go wrong?
1.2 basic tools for exploration and analysis	3.2 features to look out for and their implications
1.7 avoid being misled by data	2.1-2.3 different types of biases and extrapolation
	4.1-4.2 questions that can and cannot be answered by data
2.2 map data	3.8T distortions and bias; avoiding misleading figures
2.4 supervised learning	2.5 consequences of misclassification
2.5 unsupervised learning	5.7 effect of human factors
2.6 recommendation systems	1.3, 2.4, 4.4, 5.3 ethical issues and rules that apply to user studies

The ethical topics raised in the report can be summarized in five categories:

1. data management: privacy, security, openness (transparency), human subjects (user studies),
2. educational training: decision-making,
3. analysis: tools and implications, biases and extrapolation, supervised and unsupervised learning,
4. current events/case studies: success and disaster stories, and
5. application areas: GIS, recommendation systems.

2.4 Data Science Leadership Summit (DSLS)

The summary report of the Data Science Leadership Summit [4] states one of their goals as “to take collective responsibility in the broader effort to prepare next generation data scientists to contribute in the best interests of society.” [4, p. 1] Two of their recommendations focus on ethics:

1. the data science community should define a code of ethics (recommendation #7), and
2. the academic community should integrate ethical study into research and education programs (recommendation #8).

Participants in the summit felt that “ethics training is paramount for data scientists, especially those that will be working with data about people and with automated techniques that can have consequences on people's lives” [4, p. 20]. Similar to the curriculum defined by IDSSP [3], they recommend that students study failures as well as successful case studies. The report also includes a link to a list of university courses on ethics and technology and other resources [5].

The ethical topics raised in the report can be summarized in two categories:

1. educational training: curriculum and research programs; define code of ethics, and
2. current events/case studies: success and disaster stories.

2.5 National Academies of Science/Engineering/Medicine (NASEM)

The US National Academies of Science, Engineering, and Medicine (NASEM) report “Envisioning Data Science from an Undergraduate Perspective” [6] describes data science as a hybrid discipline requiring analytical skills, communication skills, and problem-solving skills for both technical and ethical challenges. The report states that data scientists should develop data acumen, “the ability to make good judgements and decisions with data and use tools responsibly and effectively” [6, p. 1] by both tool developers and tool users. Data acumen “is increasingly important, especially given the large volume of data typically present in real-world problems, the relative ease of (mis)applying tools, and the vast ethical implications inherent in many data science analyses” [6, p. 11]. The focus of the report is outlining principles for data science education (not materials, courses, or programs). As a core area of data science study, an entire section of the report is devoted to a discussion of ethics concerns. The report concludes with a data science version of the Hippocratic Oath.

The NASEM report section on ethical skills [6, pp. 17-18] motivates the study of ethical concerns by emphasizing that “reputable data scientists are able to show why they do their work, explain the benefits that will emerge from it, and characterize and communicate the limitations of that work” [6, p. 17]. Understanding concerns such as fairness, validity, data context, data confidence, stewardship, and privacy should be intertwined with the technical competencies students learn for managing and analyzing data.

The oath included in the NASEM report [6, pp. 31-32] “highlights aspects of data ethics and the value of incorporating societal impact as part of data science education” [6, p. 31]. A critique of the oath is that it includes unexplained terminology (e.g., “analytic nihilism” and “interventionists influence” [6, p. 32]) and may be a bit too archaic to be meaningful to modern students. Nevertheless, the NASEM report is more complete in terms of explaining why ethics is important, providing illustrative examples, and affirming the importance of societal context in more depth than any of the other reports discussed here.

The ethical topics raised in the report can be summarized in three categories:

1. educational training: developing data acumen,
2. data management: privacy, stewardship (including validity and accuracy of data), and context (biases and risk minimization for human subjects), and
3. analysis: avoiding bias (fairness), limitations of models (confidence in results).

2.6 Findings: Curriculum Reports

In this section, we characterize the coverage of categories of topics with respect to their mention in the reports. Figure 1 lists the topics in the center and the each of the reports is given in an oval connected to its respective topics via edges.

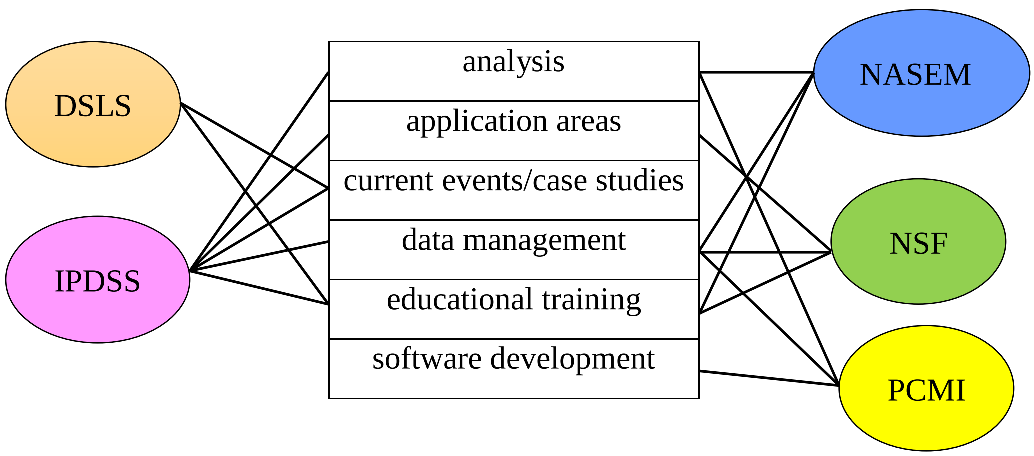

Figure 1. Ethics Topic Categories and Reports

In conclusion, while the reports acknowledge the importance of teaching ethics and identify topics for study, further effort is required before an educator can readily incorporate the issues outlined in the reports into classroom teaching and assessing of student learning outcomes.

3. Codes of Ethics for Data Science

One of the reports discussed in the previous section encourages academicians and researchers to develop a code of ethics for data science [4] while another proposes a version of the Hippocratic Oath for data scientists [6]. Most of the supporting areas for data science have professional societies with their own codes of ethics established. In addition, some more recently formed organizations have developed codes specifically for data scientists. In this section, we review and characterize the codes we identified through internet searches for “data science codes of ethics” as well as through well-known professional societies such as the Association for Computing Machinery and the American Statistical Association. They were selected because computer science and statistics are often considered two foundational areas of data science, and we expected that they would not closely overlap each other, thus providing a wider perspective in which to compare and contrast with the proposed data science codes of ethics.

There are many possible ways to describe the overlapping terminology, principles, and tenets of the codes of ethics published by various professional societies and organizations. Comparing them is not a trivial undertaking due to the variations in abstraction levels as well as the use of similar and overlapping terminology. To illustrate the complexity, we start with two of the more abstract codes that propose general principles and attempt to identify commonality and differences between the two. The overarching principles from two data science ethics sources are compared in Table 2. The principles elucidated by Matei et al. [7] appear in the column headers are and described here:

- non-maleficence: do no harm or minimize risk of harm (has primary over all other concerns),
- social justice: opportunities, rights, or goods are available to all,
- beneficence: concern for well-being of others (not necessarily required, but can be used as part of tradeoff analysis),
- autonomy: freedom and capability for individual decision-making, and
- trust: informal agreements between persons and institutions regarding expectations of behaviors.

The principles described by the Global Data Ethics Project [8] as the FORTS framework appear as the row headers in Table 2. These principles are described here:

- fairness: attention to bias in data practices,
- openness: transparent processes, community engagement, and responsible communication,
- reliability: understanding of data and its provenance,
- trust: building confidence in data practitioners using data and algorithms to maximize informed participation, and
- social benefit: considering impact of work and minimizing harm.

Table 2. Comparison of Principles [7], [8]

	non-maleficence	**social justice**	**beneficence**	**autonomy**	**trust**
fairness	x				
openness					x
reliability					
trust				x	x
social benefit	x		x		

In Table 2, the descriptions of the terms are used to identify which principles are common to both codes (with an ‘x’), and which principles appear in only one of the codes (gray highlights). The definition of social justice [7] is not explicitly addressed by the Global Data Ethics Project [8], while the opposite is true for the issue of reliability as defined [7]. In addition, some terminology that sounds similar, e.g., social justice and social benefit, are actually not synonymous based on their respective descriptions. There are also principles that occur in other codes and statements that are not in either of these two; illustrative (not exhaustive) examples of explicitly mentioned principles include: lawfulness [9], competence [9], [10], building diverse teams [11], [12], and professional responsibilities [10], [11]. There are many possible ways to describe the overlapping terminology, principles, and tenets of the codes.

In order to compare relevant aspects of codes of ethics, we illustrate how different professional societies and organizations express behavioral norms with respect to high-level criteria. In Tables 3 and 4, for data science organizations and general computing organizations, respectively, we give an example from each for (1) usage of data (protecting privacy, for example) and (2) considering impact of algorithms and techniques. These are intentionally broad criteria in order to illustrate ideas from codes of ethics (or statements of principles) that vary widely in terminology, focus, and depth.

In order to illustrate and highlight the different emphases on data ethics, algorithmic bias ethics, and professionalism, we classified each tenet of the codes referring to one of them, and then computed the proportion of each type to the number of tenets for that code. A heatmap for the data portion is shown in Figure 2. Recently formed organizations (e.g., Principles for Digital Development [13]) arising in the big data era emphasize ethical concerns about collecting and interpreting data, while more established (and more general) organizations such as ACM [11] emphasize principles of professional behavior. A heatmap for the proportion of tenets that refer to algorithms or techniques is shown in Figure 3. The codes that proportionally focus more on ethics of algorithms and/or techniques are those proposed by the Oxford-Munich Code of Conduct [9] and Data Science for Social Good [16].

Figure 4 illustrates the proportions for three primary professional organizations whose purview includes data scientists: DSA [14], ACM [11], and ASA [10]. The code of ethics provided by DSA has more balance between the three topics and thus may be a better choice for teaching data science ethics than a code intended for computing practitioners [11] or analysts [10]; however, the latter two focus more on how professionals in the respective fields should conduct themselves, which is also important for students to learn about.

The important points are that students have some appropriate set of normative behaviors for their profession and that they learn to conduct and to continue to practice ethical reasoning. Tractenberg and FitzGerald [15] suggest that exposure to pre-requisite knowledge about ethics, such as in a code of ethics, is the first step toward developing ethical reasoning skills.

Table 3. Excerpts from Data Science Codes of Ethics

organization	usage of data	algorithms and techniques
Data Science Association [14]	A data scientist shall protect all confidential information, regardless of its form or format, from the time of its creation or receipt until its authorized disposal.	A data scientist shall use reasonable diligence when designing, creating and implementing algorithms to avoid harm.
Data Science for Social Good [16]	Were the systems and processes used to collect the data biased against any groups?	What are the consequences of not acting on false negatives (and acting on false positives)?
Oxford-Munich Code of Conduct [9]	The Data Scientist shall retain copies of the original data unaltered while keeping a record describing the set of transformations made across all of the data value chain (including ingestion, cleansing, feature extraction, scaling/ normalization, feature selection, etc.)	The Data Scientist is responsible for separating correlations that are the results of chance or deliberate data-mining driven searches vs. well-established hypothesis-driven correlated information.
Data4Democracy [8]	Make reasonable efforts to know and document its [data's] origins and document its transformation.	It's my job to understand, mitigate and communicate the presence of bias in algorithms.
NASEM Hippocratic Oath [6]	I will remember that my data are not just numbers without meaning or context, but represent real people and situations and that ...	... my work may lead to unintended societal consequences, such as inequality, poverty, and disparities due to algorithmic bias.
Principles for Digital Development [13]	Addressing privacy and security in digital development involves careful consideration of which data are collected and how data are acquired, used, stored and shared.	Building sustainable programs, platforms and digital tools is essential to maintain user and stakeholder support, as well as to maximize long-term impact.
DataEthics [17]	Humans should be in control of their data and empowered by their data.	Democratic data processing is based on an awareness of the societal power relations that data systems sustain, reproduce or create.
Accenture [18]	The highest priority is to respect the persons behind the data.	Provenance of the data and analytical tools shapes the consequences of their use.

Table 4. Excerpts from Computing or Statistical Codes of Ethics

organization	usage of data	algorithms and techniques
ACM [11]	A computing professional should respect privacy: This requires taking precautions to prevent unauthorized data collection, ensuring the accuracy of data, and protecting it from unauthorized access and accidental disclosure.	A computing professional, especially one acting as a leader, should recognize and take special care of systems that become integrated into the infrastructure of society
ASA [10]	The ethical statistician is candid about any known or suspected limitations, defects, or biases in the data that may affect the integrity or reliability of the statistical analysis.	The ethical statistician acknowledges statistical and substantive assumptions made in the execution and interpretation of any analysis.
IEEE [19]	to be honest and realistic in stating claims or estimates based on available data	to improve the understanding by individuals and society of the capabilities and societal implications of conventional and emerging technologies, including intelligent systems
Linux Foundation Projects [12]	As data teams, we aim to consider carefully the ethical implications of choices we make when using data, and the impacts of our work on individuals and society.	As data teams, we aim to respect and invite fair criticism while promoting the identification and open discussion of errors, risks, and unintended consequences of our work.

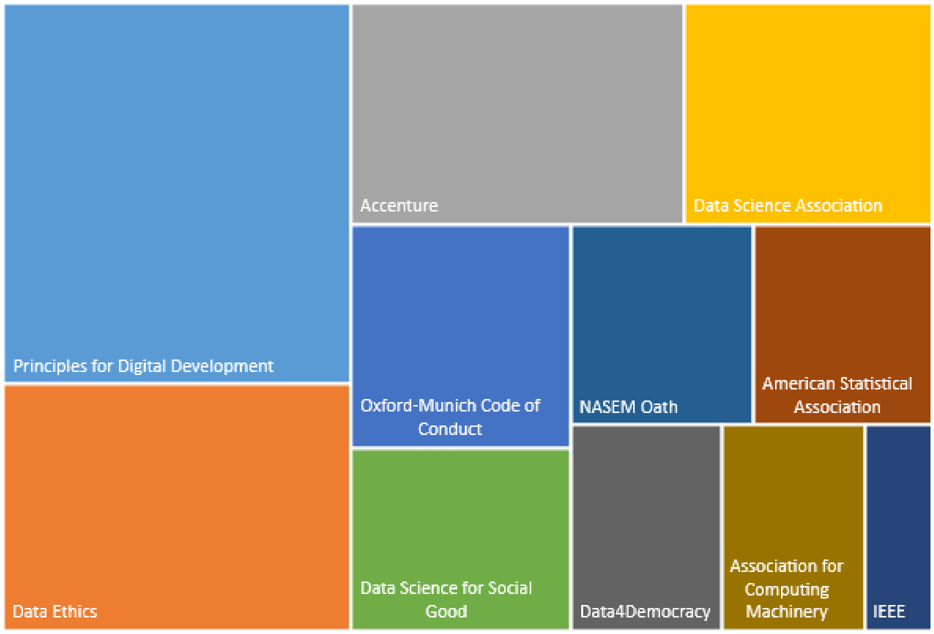

Figure 2. Proportion of Tenets Referring to Data Management

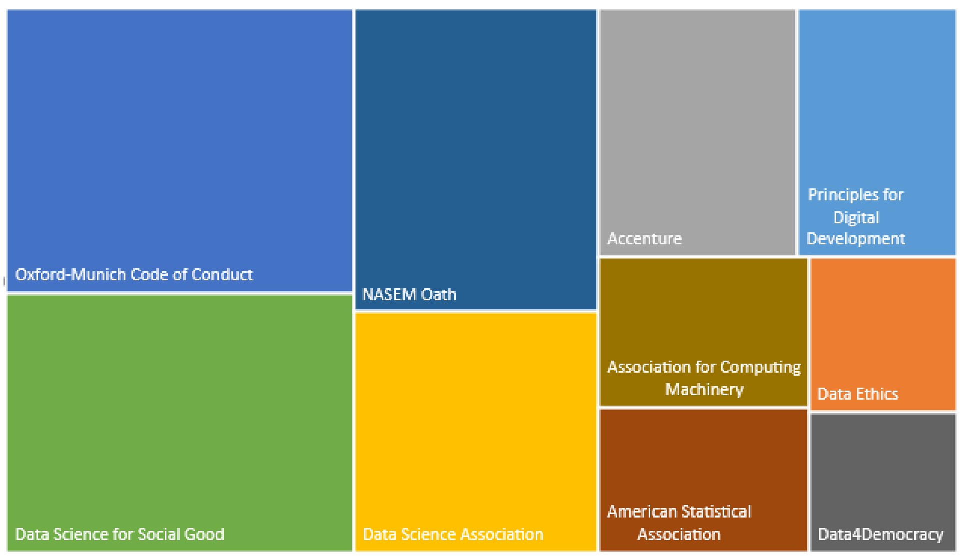

Figure 3. Proportion of Tenets Referring to Algorithms/Techniques

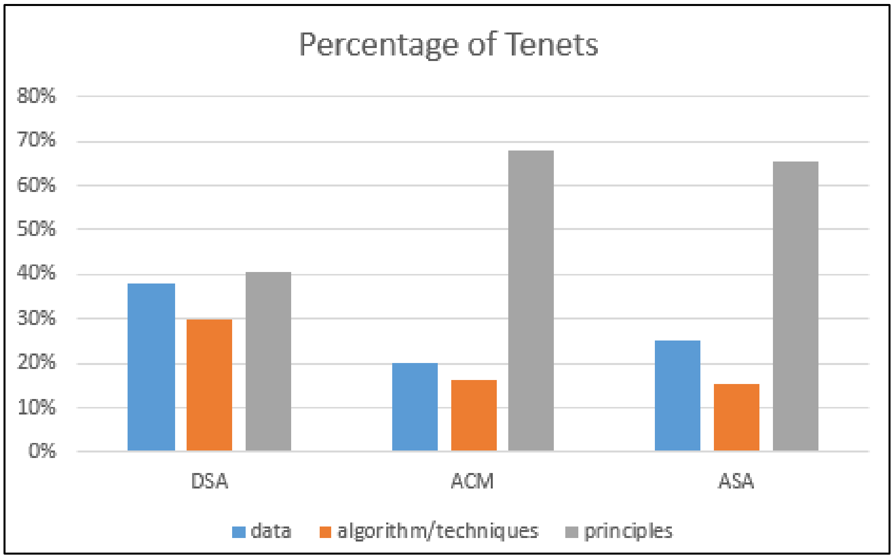

Figure 4. Proportion of Tenets about Data, Algorithmic Bias, and Professionalism

4. Teaching Ethics in Data Science

Burton et al. state that "a good technology ethics course teaches students how to think, not what to think, about their role in the development and deployment of technology, as no one can foresee the problems that will be faced in a future career" [20, p. 54]. In addition to teaching students to solve technical challenges, they need to develop skills to engage with ethical challenges arising from their professional work. A goal of teaching ethics is to equip students with the means to discuss, reason, and reflect on ethical issues. Codes of ethics define normative behavior for a professional practitioner, but a code cannot solve all problems and may even have conflicting concepts for a given situation. "Ethics education often requires a different kind of education from understanding and applying an established body of knowledge" [20, p. 58]. By also exposing students to different kinds of ethical schools of thought (descriptive ethics) and having them practice interpreting ethical issues using these theories, they have the opportunity to question and explore beyond their own assumptions. In addition, the practice supports the development of skills and habits that train students to utilize resources and processes for ethical decision-making.

In support of assessing student learning with respect to ethical reasoning, the Responsible Mastery Rubric [21] was proposed and later refined as the Ethical Reasoning Mastery Rubric or MR-ER [22]. There are 5 knowledge/skill/ability categories (KSAs) and 4 proficiency levels (novice, beginner, competent, and proficient) in the MR-ER. The KSAs are the components of developing ethical reasoning capabilities:

1. recognizing a moral issue,
2. identifying decision-making frameworks,
3. identifying and evaluating alternative actions,
4. making and justifying a decision, and
5. reflecting on a decision.

This is a process that can be applied to examining case studies or to topics encountered during specific stages in the data life cycle (shown in Figure 4) throughout a student's education in data science.

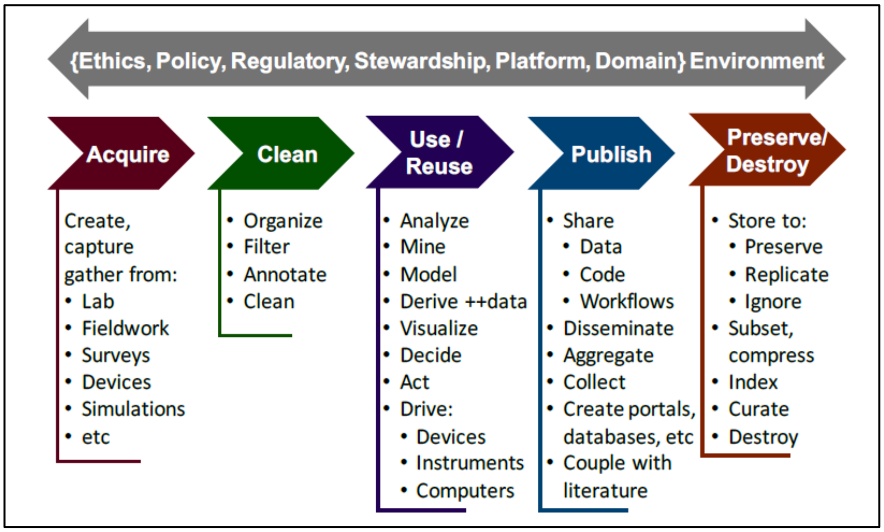

Figure 5. Data Life Cycle [1]

In our ongoing work, we are analyzing the coverage of topics in university technical ethics course syllabi [5]. We envision creating a heatmap or other visualization to show areas of common emphasis as well as to identify gaps to be filled by creation of curricular materials. Data science education needs good case studies (or even good fiction [20]) generally associated with stages in the pipeline and more specifically with techniques and algorithms deployed in technical courses. Consistent with the recommendations for intertwining ethical and technical studies [6], Tractenberg suggests that “a one-time ethics training ‘vaccine’” is not ideal [21], but rather creating a culture of ethical practice through repeated and consistent exposure, aligned with their technical training, would produce data scientists better prepared to engage with the challenges to be faced in their future professional lives.

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