Computing Ethics Narratives:

Teaching Computing Ethics and the Impact of Predictive Algorithms

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ABSTRACT

The prevention of criminal activity has changed dramatically over the past two decades, largely due to the increased reliance on systems that provide crime data analysis. Created specifically for police, judicial sentencing, and prison applications, these systems conduct both predictive and retrospective analysis to aid decision making within the criminal justice system. Furthermore, these software platforms typically combine spatial informatics packages and advanced statistical features behind user-friendly interfaces. Recent studies have demonstrated problems with both the flawed logic within these systems' algorithms and the inherent biases in the underlying data. In this paper, we present a novel repository of computing ethics teaching modules across a variety of narrative areas. These modules and curated narratives help faculty to establish "ethical laboratories" that can guide computer science students in improving their ethical reasoning skills as it relates to the creation of current and future technologies. First, we provide an overview of the Computing Ethics Narratives (CEN) project, its narrative repository and the module framework through a sample module on predictive policing algorithms. Furthermore, we share preliminary findings from a pilot of this module, which was implemented in an intermediate algorithms course. The preliminary student and faculty feedback suggest the predictive policing module was able to help students contextualize the ethical issues around the topic, however, students recommended devoting more class time to evaluating the technical complexities of these critical systems.

CCS CONCEPTS

• Social and professional topics → Computing education • Social and professional topics → Code of Ethics

KEYWORDS

Computing Ethics; Predictive Policing; Teaching Resources

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1 Introduction

Although the critical nature of embedded ethics instruction within computer science (CS) curricula has been well established over the last fifty years, there remain significant barriers to infusing evidence-based ethics instruction across core, undergraduate CS content areas. These barriers include competing domain approaches, minimal evaluation of approach effectiveness, and resistance among many CS faculty to the integration of ethics instruction into core course content. The goal of The Computing Ethics Narratives project (CEN) is to provide a pedagogical framework with an emphasis on integrating computing ethics instruction through an interdisciplinary lens. The project is grounded in the construction of narratives as "ethical laboratories" that allow students to experiment with the ethical implications of a given plot [1].

This paper describes a module designed for an intermediate level Algorithms course; however, it could also be integrated into a variety of other core CS courses such as Data Structures, Data Science, or a stand-alone Computing Ethics course. This particular module introduces students to the technical, cultural, and ethical issues of predictive policing algorithms. After a brief overview of the CEN project, and a review of the history, types, and technologies associated with predictive policing algorithms, we present the module learning objectives, instructional framework, activities, and pilot evaluation. The module presents multiple perspectives around the ethical issues associated with predictive policing algorithms, including the use of potentially biased datasets, and minimal human oversight that may violate the professional codes of ethics for both software developers and law enforcement professionals.

2 Computing Ethics in CS Education

The evolution in approaches to defining and teaching computing ethics has been well documented [2-5] and yet there remain significant barriers to infusing evidence-based ethics instruction across the core CS curricula. These barriers include a lack of evidence-based evaluation of approach effectiveness, the absence of easily accessible instructional resources (beyond textbooks and journal articles), and faculty citing insufficient instructional time available to devote to integrating computing ethics curriculum as part of the core CS content. Connolly [6], in particular, critiques most traditional models of teaching computing ethics as only providing a light treatment of ethical theory and its application in the analysis of the impact of a specific type of technology. What this approach offers in its simplicity for CS faculty to implement, it lacks in its ability to convey the complex and fluid relationships between technology and societal dynamics. [7] Yet, throughout modern history, innovations in computing are situated within a cultural context, as shapers of and reactions to social forces such as class, race, and gender. These complexities are often ignored in many traditional CS ethics courses in favor of legal, professional, or surface level philosophical treatments [8-9]. New approaches to computing ethics are emerging, largely driven by interdisciplinary teams of faculty and students from computer and information science, philosophy, social sciences, and the arts. For example, the Embedded EthiCS initiative embeds philosophy graduate students and post-doc fellows within the core computer science courses to provide mini-module instruction and repeated opportunities to examine and reason about the ethical issues inherent in technological design and development processes [10]. Several more initiatives use narrative forms of science fiction and theatre to engage computer science students to reason about potential impacts of past, present or future technologies on fictional societies [11-16].

The CEN project, described in this paper, builds upon this body of existing work with two significant additions: 1) a focus on how narratives can help to students to examine their own roles, responsibilities, biases and ethical reasoning skills through a critical CS ethics feedback loop during the design, deployment and testing processes, and 2) development of a searchable, annotated multi-media archive for CS faculty and students to access and store narratives, instructional resources, and modules for teaching computing ethics in core CS courses [17]. Below are the working definitions of the CEN module concepts, curriculum elements, and their relationships to one another that will be described in the remainder of this paper:

Narrative: A historical (past and present), fictional, or real-world story/perspective involving technologies.
Narrative Area: Sets of narratives grouped by societal themes (e.g., Algorithmic Bias, Government Civil Surveillance, Telemedicine, Artificial Companionship and Therapy, etc.).
Technology Area: Sets of narratives grouped by functionality and are based on the technologies they employ. These are loosely aligned with ACM Computing Classification System (CCS). (e. g., Biometrics, Robotics, AR/VR, etc.)
Module: A pedagogically cohesive set of activities designed to enhance students' ethical sensibility on evaluating issues associated with technologies and their role as a technology creator.
Activity: A pedagogical intervention that is part of a module. Activities typically refer to one or more narratives.
Repository: A tagged, annotated, and searchable database that connects narratives with associated modules and retrieval sources.

3 Theoretical Framework

With the spread of ubiquitous computing devices, efficient wireless communication networks in vast areas of developed countries, and remote distribution of digital applications and content, technological innovations directly impact the lives of billions of people overnight. These same technologies have produced changes in the way people use their time, interact with one another, and how they experience the physical environment. The CEN framework is grounded in the idea that students and faculty need to engage in continuous ethical reflection that considers: 1) specific aspects of technologies from the design phase to distribution and, 2) the human and ecological contexts that will be impacted by technologies.

The CEN framework consists of several ideas that are central to the module rationale. First, the use of the plural form of technologies stresses the attention to unique characteristics and impacts of specific tech artifacts. The ethical implications of automated coffee machines are different from a voice interface home assistant built on AI algorithms and sending data to a server located thousands of miles away. Even though both technologies fall under the automated home devices and often sit next to each other on a new kitchen countertop, the consequences and the use of these technologies carry different levels of both trust and risk. Second, computer science students need to understand the context of these technologies within current and near future cultural and social phenomena, informed by critical theory on gender, race, and class. Finally, students need sustained assistance in developing an ethical sensibility to interpret the power and privilege they embody as tech creators through the design and production of new technologies as well as how these tools modify the way we live, think about, and experience technologies.

4 Computing Ethics Narratives (CEN)

The CEN project is funded by the Mozilla Foundation's Responsible Computer Science Challenge [18]. This national initiative is supported by a number of tech industry and private foundations to support computer science faculty in the development, and piloting of curricula that integrate ethics with undergraduate computer science training, in order to increase holistic thinking about technology design, deployment, and testing policies and practices.

4.1 CEN Repository

The CEN repository is organized around the concept of a collection of *narratives* defined as historical (past and present), fictional, or real-world stories and perspectives involving technologies. Each narrative belongs to at least one or more *narrative areas or s*ets of narratives organized by themes.

Narratives also belong to one or more *technology areas* or groups of narratives that are based on the technologies they employ. A *CEN module* is a pedagogically cohesive set of activities designed to enhance students' ethical sensibility on evaluating issues associated with technologies. Each *activity* uses one or more narratives from the *repository.*

Currently, the CEN repository has links to approximately 700 narratives comprised of links to hosted film clips, short stories, news articles, blog posts, television series episodes, presentations, book citations, journal articles, podcasts, and reports. The repository architecture is integrated with an existing Bowdoin College resource, Kinolab [19]. Kinolab was created as a way for academic faculty teaching film studies to store, annotate, organize, and share film clips with their students in a searchable database that complied with Digital Millennium Copyright Act of 1998 (DMCA) regulations [20]. The CEN repository models the key concepts of the computing ethics framework and integrates it into the narratives stored in the database and Kinolab stores the video narratives for viewing while the repository stores the links to the text narratives.

4.2 CEN Website

The CEN website will provide a gateway into the modules, narratives, and conceptual areas that would be most relevant to teaching computing ethics. The website prototype is designed to allow instructors to use existing modules as is, browse the narratives by area or media type, search for modules or narratives by technology area, add new narratives through an online curation process, and create new modules through the user interface. The website will be secured through a password protected interface designed to accept user membership through a verified higher education institutional email address. It will also seamlessly connect users to media stored in Kinolab so that users can navigate from the narrative descriptions to the video-based narrative content.

4.3 CEN Modules

All modules are based on a set of lessons and activities that provide students with opportunities to explore the ethical questions and impact around an existing or emerging technology from the perspective of future creators of technological innovations. Each CEN module, and each activity within the module, is based on a set of student learning outcomes. For example, the Predictive Policing Algorithms module has a set of specific learning objectives designed to help students develop an 'ethical sensibility' around their role in the creation and use of predictive algorithms that have a potential for large scale societal impact.

5 Predictive Policing Systems

Critical theory on the use of predictive systems in current policing and sentencing practices situates these technology artifacts within systems of power that reinforce and perpetuate historical and societal inequities [21-23]. A full review of critical race theory as it relates to role of predictive policing is beyond the scope of this paper, however, we do include module narratives that critically examine computing concepts such as testing for algorithmic biases in datasets and developing algorithmic examples that demonstrate specific structural inequities using real world data [24-26].

At their core, predictive policing algorithms are forecasting models that use historical data and feedback to make predictions about "where and when crime will occur, or who might be a perpetrator or a victim" of a crime [27]. Like all models, predictive policing algorithms rely on big data, usually provided by police departments themselves, and feedback to refine the accuracy of future predictions. Predictive policing algorithms provide a compelling 'ethical laboratory' for a narratives module to engage students in thinking through the impact of predictive algorithms from a multitude of perspectives. Students can explore the development and use of these algorithms from a historical narrative perspective (evolution of the software systems), a societal narrative (focusing on the community impacts of predictive policing algorithms), a technical narrative (exploring the data and algorithmic design of predictive policing algorithms), and a fictional narrative (examples found within popular culture media).

Law enforcement agencies, politicians, public policy researchers, and criminologists have developed countless theories and models to predict crime. The New York Police Department's (NYPD) 'stop-and-frisk' model in the 1960's and it's 'zero-tolerance' policy against minor crimes and gun offenses during the 1990s [28] are examples of such predictive strategies. When New York implemented its random, stop-and-frisk model, the number of stops rose 600 percent in comparison to the previous decade. In fact, 9 out 10 of the individuals stopped and frisked by the NYPD in 2011 were innocent of any crime [29-30]. Subsequent analysis revealed that Black and Latino citizens were subject to a disproportionate number of stop-and-frisks conducted by the NYPD. As for the outcomes of these policies, not only did the NYPD's tactics fail to produce major decreases in crime or gun violence, but they also perpetuated historical cycles of oppression for the city's minority communities. Citing the inefficiencies and biases of models like stop-and-frisk policies, current predictive policing software companies market their products as the most efficient tools for budget-constrained departments covering diverse, urban areas. These systems fall into two broad algorithmic design approach categories: Person-based and Place-based algorithms.

5.1 Person-based Algorithms

Introduced in 2009, person-based policing algorithms aim to identify potential suspects and victims of crime [31]. The Chicago Police Department (CPD) employs this form of predictive policing system, using it to develop their *Strategic Subjects List* (SSL). Based on CPD arrest data and social network theory, this list ranked approximately 400 individuals based on a threat score, which was determined by an individual's connections to victims of gun-related crimes. Police officers then interacted with individuals to supposedly prevent violence before it is able to occur.

5.2 Place-based Algorithms

Place-based policing algorithms use a variety of approaches to analyze crime data based on geographical regions [32-33]. PredPol [34], uses crime occurrence data, including location, date, time and type of reported crimes, to predict potential crime levels in specific areas. For system feedback, the algorithm uses arrest data to determine if the prediction was accurate. HunchLab [35] incorporates historical and current data to guide patrol units. According to its promotional material, HunchLab considers a multitude of data points in its model, such as the number of bars within an area, weather patterns, and "socio-economic indicators" [36]. These algorithms typically visualize the data model output using heat maps to optimize resources for the prevention of potential 'future' crime.

The companies selling predictive policing software promise their product can help law enforcement to fulfill arrest quotas, close more unsolved cases, and identify potential 'persons of interest' to prevent future crimes without having to hire more police officers. This goal of preventing future crimes is not unlike the plot of the P.K. Dick's 1956 short story narrative 'Minority Report' [37] and the 2002 film adaptation by the same name [38], both depicting the ability of technology to predict and stop 'pre-crime'. These types of narratives about technology and its impact on society provide ways to engage students in ethical laboratories to examine, think through, and discuss both fictional and real-world ethical issues as the creators of future technological innovations that can directly influence lives in profound ways.

6 Predictive Policing Module

This module is organized around the use of narratives, real-world datasets, group discussions, and individual reflections. Student learning objectives for each CEN module focus on ways in which students: 1) identify the potential ethical impacts (intended or unintended) of predictive policing algorithms, 2) check for biases in logical assumptions and datasets, and 3) develop ways to prevent and mitigate the potential harm of predictive policing algorithms.

6.1 Prefiguration (Activity 1)

All modules begin by assessing what students know about a computing ethics topic and/or technology. We refer to this part of the module as prefiguration (Activity 1) based on Ricoeur's concept of finding common ground between language and culture [39], where we collect baseline data on student preconceived ideas and existing knowledge about the topic area in a short, online writing assignment administered through the course learning management system (LMS). This assignment focuses on opening up a space for students to reflect on what they know about a topic, both as an individual and as a class. In this module, we ask students to answer the following questions:

- What are the positive aspects (present or potential future) of Predictive Policing systems? Please list as many as you can.
- What are the negative aspects (present or potential future) of Predictive Policing systems? Please list as many as you can.
- Considering the two lists you just made, what kinds of impacts do you think these Predictive Policing systems have on individuals and on larger society?
- Who were these systems designed by and what are the values reflected in this technology?
- Who were these systems intended to be used by?
- What do you know about the current uses of these systems?

After the prefiguration assessment has been collected and reviewed, the instructor would briefly ask students to share their existing knowledge (either in a face-to-face class setting or during an online class session) on what predictive policing algorithms are, how they are designed, and for what purpose (again, no more than a 15-20 minute discussion). In this stage of the module, we are collecting baseline data to help measure any potential changes in the number of different points of view, types of themes, and counter perspectives the students are able to coherently express when they describe ethical aspects of a given technology.

6.2 Configuration (Activity 2)

Narratives configure, through their plots, possible worlds in which we can inhabit. The configuration itself is part of the author's creative process [39]. Activity 2 features a hands-on activity and a longer, more interactive session exploring the topic. The second stage of the module typically occurs 1-3 days after Activity 1 to provide students with some time to review a set of narratives representing a variety of perspectives on the topic/technology that are pulled from the CEN repository. Activity 2 focuses on presenting students with additional information and/or resources to explore the potential ethical issues that are involved with the target technology. Learning outcomes of this lesson focus on the synthesis of the narratives, analysis of results presented by real-world data, as well as individual and group decision-making based on the results. The modules are designed to be flexible in their timing, enabling the instructor to manage all core course content and assignments that might need to occur before the next CEN Activity. For example, in the Predictive Policing Algorithm Module, we created an activity where students are provided with real-world crime data from the city of Oakland, CA and are guided through an analysis of the data demonstrating the various issues with the dataset that may lead a predictive algorithm system to produce inaccurate results and influence police actions and decision making.

Students are divided into groups of two to three and each group is given one of three Oakland Police Department datasets representing a single year of crime data. Students receive detailed instructions on how to import the dataset into a statistical package and are led through a series of exercises to analyze and visualize their data in order to simulate a predictive model:

- analyze crime reports for measures of central tendency,
- identify police patrol areas with city zip codes,
- identify high crime areas by zip codes,

- link racial and socio-economic demographic data for these areas with data from the U.S. Census,
- calculate percentages for areas of racial group over/under representation and low/high income
- present their findings to share the demographics of the types of areas that a predictive policing algorithm would highlight and ignore.

6.3 Refiguration (Activity 3)

In the module's refiguration activity, students are asked to consider additional narratives in relation to the previous guided activities [39]. In some of the modules, it might be fictional narratives such as extended film clips or short stories that present additional perspectives. In the case of the Predictive Policing module, we use existing professional codes of ethics to contextualize the discussion around predictive policing algorithms, the creation of such algorithms by software engineers, and their current use by law enforcement agencies.

Both law enforcement officers and software engineers are regulated by codes of ethics that outline their ethical responsibilities. For law enforcement officers, the code of ethics adopted by the International Association of Chiefs of Police (IACP) offers a set of standards for the profession [40]. The IACP is a non-profit organization focused on the advancement of law enforcement and crime prevention in more than 150 countries around the world. Despite the pervasiveness of the IACP, states and precincts are not required to adopt any ethical code surrounding the ethical use of crime data in policing practices. However, the State of California does recognize the Law Enforcement Code of Ethics and uses it to regulate the policies, practices, and actions of its police officers, therefore, it is useful for students to view the Oakland case study specifically through the lens of the IACP's code of ethics [41].

As the designers and creators of such technology, computing professionals are also responsible for the ethical design of decision-making tools based on various codes defined by professional computing and engineering organizations, including the Association of Computing Machinery (ACM). The ACM Code of Ethics and Professional Conduct [42] provides guidelines as to how computing professionals should make technical and leadership decisions to positively impact society. The newly revised code of ethics stresses the need for software engineers and computing professionals to consider societal impacts when making technical decisions. Specifically, the code clearly states that engineers must acknowledge that all people are stakeholders in computing. Using these two professional codes of ethics, students are asked to consider these professional narratives to identify and address the potential ethical ramifications of predictive policing algorithms during the design, deployment, and testing phases.

At the beginning of Activity 3, the instructor provides 20 minutes for an in-class writing assignment to measure the changes (if any) in the narrative density and response themes. The assignment is the mechanism through which the readers of narratives (i.e., students) expand their interpretation of the world by reassessing their prefigured world views after the contact with the configured narratives. In the case of the Predictive Policing Algorithms module, the instructor would ask students to revisit several of the questions posed at the beginning of the module as well as an additional question asking about any change in thinking the students may have experienced over the course of the module.

The assessment of a module's student learning outcomes can happen in a variety of ways depending on the size of the class, the availability of course support (e.g., Graders), if it is administered through an in-person or online format, and the level of details that are appropriate for the instructor's learning goals.

7 Discussion: Pilot Module Implementation

During the Stage 1 of the CEN project, eight modules, including the Predictive Policing module, were developed and piloted with CS undergraduates. Each module was administered in the three activity segments to courses with a range of 8-30 students. The open response data collected from students (n = 24) during the pre- and post-assessment phase of the predictive policing module did indicate a small degree of change in individual student awareness of the impact of the predictive algorithms. We focused on coding the themes raised in Question 1 and 2 (positive and negative aspects of the technology) and the students' perceptions of the technology's impact on society conveyed in Question 3: "Considering the two lists you just made, what kinds of impact do you think these Predictive Policing systems have on individuals and on larger society?" As a whole class there was a far stronger negative impact response on society cited by students in the post-assessment than the pre-assessment. Predominant themes in the pre-assessment responses centered on concepts such as *'saving lives', 'preventing terrorist and school shooting attacks', 'increased efficiency of police time and resources'*. In the post-assessment responses, the most frequent responses were clearly focused the negative impact of these systems and as reflected by themes such as the *'perpetuation of racial injustice', 'increased reliance of decision making on biased or bad datasets', and 'valuing efficiency over accuracy and fairness'*.

The students were also asked to provide feedback about their overall learning experience during these three module activities, if they felt it was connected to the course objectives, and what suggestions they might give for the next iteration of the module. Overall, students reported the module provided important background information on the topic and did connect to the course content. However, they felt the implementation of the activities, especially Activity 2 (data analysis), could be improved by being given more class time to examine a predictive algorithm that was similar to the ones used in the proprietary systems under discussion rather than just looking at the ways the datasets were flawed and biased. They felt more time could be spent devoted to this type of analysis to make the module more meaningful.

Instructor feedback was collected through a survey that consisted of seven Likert response questions, a ranking of module effectiveness on a scale of 1-4 (1=not effective to 4=highly effective), and five open response questions. The CS instructor for this pilot module reported that they felt the CEN module content was valuable, the activities were balanced, the module content was aligned with their core course content, and it was something they would use in the future, as well as recommend to other CS instructors. The only question that the instructor ranked as uncertain was whether the module helped to increase student learning and engagement in their course. For the open response questions, the instructor reported that they believed ethical issues related to algorithms was an important topic and that the pilot modules helped to fill a gap in the course content. They also indicated the future versions of the module should include the opportunity for students to examine and work with similar predictive policing algorithms in order to help to tie the module to the rest of the course content more strongly. The pilot evaluation feedback will not only help to improve future module implementations, but also refine the ways in which this module can be delivered effectively in both an in-person and online format. In particular, we hope to update the set of module narratives to reflect current reforms and legislation around the use of predictive policing systems, the impact these algorithms continue to have on marginalized communities, and their intersection with systemic racism structures in the U.S. [For narratives used in the 2019 pilot module, see references [43-49].

7 Conclusion

Creating engaging content across the core computer science curricula related to the ethical implications of computing professionals' decision-making is critical for creating well-designed and responsible technologies. Computer science students rarely receive more than a single course in computing ethics, the breadth of which is too large to dig deeply into specific ethical questions as they are learning core technical content. In this paper, we present an alternative model for engaging students in ethical reasoning across the core CS technical curricula through the teaching of ethics using Ricoeur's ethics narratives framework [1]. From the introductory to advanced levels, we hope the CEN modules will help students to develop an 'ethical sensibility' by guiding them to consider multiple perspectives through different narratives and considering the ethical implications as well as their personal responsibilities as creators of future technological innovations that will have a profound impact on society. Engaging future technologists in sustained and meaningful discussions about the ethics of current and near future technologies allows them to become active participants in societal conversations and informed architects of policies, practices, and regulations. Future work planned for the CEN project includes the development of additional modules, the expansion of the CEN repository to include additional narratives, narrative and technology areas, and computing ethics education resources to support CS faculty in developing their own modules based on this framework.

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APPENDIX 1: MODULE NARRATIVES

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