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Board 74: Using Machine Tools to Analyze Changes in Students' Ethical Thinking

Dr. Roman Taraban, Texas Tech University

Roman Taraban is Professor in the Department of Psychological Sciences at Texas Tech University. He received his Ph.D. in cognitive psychology from Carnegie Mellon University. His interests are in how undergraduate students learn, and especially, in critical thinking and how students draw meaningful connections in traditional college content materials.

Dr. William M. Marcy P.E., Texas Tech University

Professor and Director of the Murdough Center for Engineering Professionalism and The National Institute for Engineering Ethics Texas Tech University Lubbock, Texas

Mr. Lakshmojee Koduru,

I am a Data Scientist at Schneider National where I build predictive models for the Transportation and Logistics.

John Richard Schumacher, Texas Tech University

I am a PhD in Cognitive Psychology at Texas Tech University. My primary research interests lie in studying memory as it applies to an academic setting, and moral decision making. I also have a strong interest in studying different statistical analytical techniques to appropriately and efficiently model data.

Micah Iserman, Texas Tech University

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Abstract

Engineering ethics education entails the development of the ability to recognize the social, cultural, environmental, and global implications of engineering practice. Instructional activities often involve discourse among students and verbal and written responses to ethical issues and dilemmas. The present research applies two machine methods to extract the dominant concepts in engineering undergraduates' essays that were written at the beginning and end of an engineering ethics course. The two methods were Linguistic Inquiry and Word Count (LIWC) and naïve Bayesian analysis. Both methods showed little overall change in the conceptual basis of beginning versus end of semester essays. Closer analyses of the Bayesian results suggested there were observable individual differences in the essays. Further analysis of these differences may aid in better understanding which students changed their ethical thinking from the beginning to the end of the course. In the Discussion we suggest several ways in which success with these machine methods could aid instruction.

1.0 Introduction

Part of being a responsible engineer involves the ability to act ethically across a broad range of situations. In U.S. engineering education, ABET (Accreditation Board for Engineering and Technology) criteria for accrediting instructional programs lists ethics as one of the critical learning outcomes. Student outcomes include "an ability to recognize…," an ability to "make informed judgments," and "an ability to apply…," essentially covering the gamut of cognitive knowing, judging, and implementing. What is striking about these ABET goals for student outcomes is the coordination of engineering practices with a full range of social, cultural, environmental, and global considerations.

> ABET 3.1 *an ability to apply engineering design to produce solutions that meet specified needs with consideration of public health, safety, and welfare, as well as global, cultural, social, environmental, and economic factors*
>
> ABET 3.3 *an ability to recognize ethical and professional responsibilities in engineering situations and make informed judgments, which must consider the impact of engineering solutions in global, economic, environmental, and societal contexts*
> https://www.abet.org/accreditation/accreditation-criteria/criteria-for-accrediting-engineering-programs-2019-2020/#GC3.

Through these ABET criteria, engineering education is clearly tasked with addressing the broad implications of engineering practice. This is often achieved through the discussion of engineering case studies [1] [2], including classic conflict problems like that portrayed in the video "Gilbane Gold," which was produced by the National Society of Professional Engineers (NSPE). Instilling ethical thinking into engineering students is also achieved through a consideration of the types of cases they are likely to encounter in professional practice. Discussion among students and making judgments are important for ethical development. According to Harris [1], "If a professor of engineering gives students a chance to make ethical judgments, explain them, and compare them with those other students make, the student is more likely to judge well than if she gets no such experience" (p. 94). The goal of this paper is to consider two methods of automatically assessing the content of students' verbal interactions in an engineering ethics course using machine methods. These methods can be applied to transcribed verbal interactions from discussion groups or to written reactions, like open-ended essays. The present paper focuses on the latter type of data.

1.1 A Key Principle

A fundamental computational principle underpins a wide-range of intelligent machine-based systems, including the two that are examined here. Stated simply: *There are highly probable markers (cues, features) in the input (e.g., student essays) that characterize key constructs in the input*. Case studies, like the present, exploring this principle have theoretical and applied implications. On a theoretical side, deeper insights into the manifestation of this principle in computational models increase our understanding of how human classification, organization, and production of ideas might take place. From an applied perspective, better understanding of this principle gives instructors leverage in configuring and implementing instructional activities. Having a better grasp of the key constructs that students are employing potentially aids instructors in understanding why a specific activity is effective.

The primary research questions are:

- How reliable are machine methods in extracting the substantive constructs – i.e., what the student is communicating in ethics classwork?
- How might successful application of these methods aid ethics instruction?

2.0 Background and Literature Review

In recent years, engineering organizations, institutions, and disciplines have become more concerned with equality and inclusiveness, and with the effects of engineering on the concerns and experiences of a broad swath of individuals and communities. Two major areas characterize current research in determining how to best prepare engineering students for ethical professional practice. One issue involves the fundamental nature of engineering ethics, like care ethics in the work of Warford [3] and Nair and colleagues [4] [5], empathy and care in Hess, Strobel, and colleagues [6] [7], and reflexive principlism in Beever and Brightman [8] [9]. The other issue involves developing effective methods to assess changes in ethical thinking as an outcome of instruction. Structured rubrics for assessing ethical reasoning include specific factors like Identification, Justification, Specification, and Perspective-Taking, in Hess, Beever, and colleagues[10], and Relevance, Argumentation, Complexity, and Fairness in the work of Sindelar, Shuman, Besterfield-Sacre, and colleagues [11] [12].

2.1 Fundamental Nature of Engineering Ethics

Major themes in ethics education encompass professionalism, following an ethical code, and doing no harm [13] [14] [15]. More recent scholarship has emphasized the importance of working from a perspective of empathy [6] [7], following a care ethic [3] [4] [5], and being socially aware and responsible. Research in the engineering education literature has addressed effective content for classroom instruction [1], how students learn ethics

[16] [17], and demonstrations of how ethics can be learned and practiced in real-world contexts [18].

Globalization affects the perspectives that engineers take on ethical issues. Lynn and Salzman [19] suggest that nationalistic and isolationist policies are counter-productive. The goals, rather, should focus on accepting diversity in the workforce, forming collaborations with other countries, and participating in global innovations. Achieving these goals requires "a broad education that incorporates a range of technical and social science and humanities knowledge," "an appreciation for other cultures," and "more ethical treatment of those who are different." It is now becoming more widely acknowledged that engineering decisions require a sense of social justice, fairness, and equality from a global perspective [18] [20] [21]. Responsible and well-designed engineering projects, according to Baillie [20] are sensitive to the economic, social, and political factors at local and global levels.

3.0 Machine-Based Assessment Methods

The present paper considers machine methods for assessing changes in students' ethical thinking after course instruction. There are generally three types of methods of machine analysis of texts: using a pre-defined database, applying supervised learning methods, and applying unsupervised learning methods [22]. One of the best known methods for applying a predefined database was developed by Landauer and Dumais [23] [24] [25] under the title of Latent Semantic Analysis (LSA). LSA calculates the semantic similarity between texts using high-dimensional semantic representations. The texts that are compared can be words or larger chunks of text, like essays. One shortcoming of LSA is that the similarity between texts is reported in terms of vector similarity (i.e., cosine similarity) [24]. Practically speaking, when using LSA it is not possible to identify the specific words (alternatively, concepts) that are the basis of the computed similarity.

Another well-known method for text analysis, LIWC (Linguistic Inquiry and Word Count) [26], uses predefined dictionaries. LIWC quantifies the frequencies of words (or stems) that fall into specific categories, like cognition, positive emotion, and biological processes. These frequencies can then be correlated with independent variables, like likelihood of academic success [27] [28]. For example, Carroll [29] applied LIWC to students' essays in a sophomore-level critical thinking course and found differences in affect in students' essays at the beginning compared to end of semester. One concern that arises with the application of LIWC is whether the pre-defined dictionaries that LIWC draws on are appropriate for the texts that are being analyzed. The essays that students compose in specific courses, for instance, may more strongly reflect concepts (as signaled by the words they use) in that course, and those concepts may not have been adequately anticipated in the development of LIWC.

An emerging supervised method for text analysis uses naïve Bayesian computations. The method is based on an extension of Bayes theorem and is used to create classifiers that identify predictors that are able to classify old and new instances. For instance, after training on a set of newspaper editorials written from reactionary and liberal perspectives, a Bayesian classifier can be used to classify new editorials based on the discriminating predictors within the texts. The appeal of naïve Bayesian classifiers is their capacity to be trained to classify content in specific subject domains.

4.0 Case Study Applying LIWC and Bayesian Analysis

The present study tested LIWC and naïve Bayesian analysis. Data for this study were generated by posing the same question to students at the beginning and end of an engineering ethics course. The empirical question was whether LIWC and naïve Bayesian analyses could identify changes in students' thinking about ethics from the beginning to end of the course. LIWC and naïve Bayes were chosen because these methods allowed for the recovery of the discriminating words (concepts) that were used to separate the texts into classes.

4.1 Course and Materials

The materials for analysis were drawn from a sophomore-level ethics course at a large public Research 1 (Carnegie classification) university. This course is required of most engineering majors. Ethical reasoning is developed through an introduction to ethical theories and contemporary ethical issues in engineering, technology and society. Course materials and assignments consider *intuitionism*, which is a person's intuitive reaction to ethical issues, three ethical theories – i.e., utilitarianism, respect for persons (Kantian deontology), and virtue ethics – and the National Society of Professional Engineers (NSPE) code of ethics. Through a variety of activities and formats, students analyze and respond to ethical issues in contemporary social settings involving engineering technology and practice.

4.2 Participants and Procedure

The present study used a pretest/posttest design. The participants were 125 undergraduates enrolled in the ethics course in the spring 2018 semester. Near the beginning and end of the course, students wrote essays about what it meant to be a professional ethical engineer, in response to the prompt: *In some detail, describe the attitudes and behavior you would expect of an ethical engineer. Your response should be a minimum of 300 words but not more than 500 words.* Of the 125 students, 98 completed the pre and post essays. Students who did not complete both essays were eliminated from further analysis.

Students' pretest and posttest essays were analyzed using the 2015 version of LIWC, which is available at the website http://liwc.wpengine.com/, and naïve Bayes analysis using the R language https://www.r-project.org/ through R Studio https://www.rstudio.com/ and including available libraries that can be downloaded into R Studio. LIWC applies predefined dictionaries. In the present analysis, LIWC was used to calculate percentile scores for four variables: analytic thinking, confidence, self-disclosure, and emotion. Naïve Bayes was trained to identify predictors in a sample of essays and was then tested using a new sample of essays.

4.3 LIWC Results

The four variables that were tested using LIWC are defined as follows in the LIWC Manual [26]:

- **Analytic Thinking -** A high number reflects formal, logical, and hierarchical thinking; lower numbers reflect more informal, personal, here-and-now, and narrative thinking.
- **Clout -** A high number suggests that the author is speaking from the perspective of high

expertise and is confident; low Clout numbers suggest a more tentative, humble, even anxious style.

- **Authentic -** A higher number is associated with a more honest, personal, and disclosing text; lower numbers suggest a more guarded, distanced form of discourse.
- **Tone -** A high number is associated with a more positive, upbeat style; a low number reveals greater anxiety, sadness, or hostility. A number around 50 suggests either a lack of emotionality or different levels of ambivalence.

Means and standard deviations are shown in Table 1.

Table 1. Means (standard deviations in parentheses) for LIWC Variables, by Type of Essay (N = 98)

LIWC Variables	Beginning of Course Essay	End of Course Essay
Analytic	75.01 (15.10)	75.28 (16.54)
Clout	62.12 (13.93)	60.64 (13.87)
Authentic	11.78 (11.43)	11.16 (11.40)
Tone	68.65 (26.62)	70.85 (23.72)

An analysis of mean differences using the GLM procedure in IBM SPSS Version 24 https://www.ibm.com showed significant differences between LIWC variables [$F(3, 291) = 405.73$, $p < .001$], but non-significant differences between the type of essay (beginning vs end of course) [$F(1, 97) = .01$, $p = .925$], and a non-significant interaction of type of essay and LIWC variables [$F(3, 291) = .65$, $p = .578$]. What is striking about this outcome is the close similarity of the mean variable scores for beginning and end of course essays. These results show that LIWC was able to find differences within the essays in terms of analytic thinking, confidence, disclosure, and emotion, as indicated by the highly significant differences between variables, but LIWC did not detect differences in how students wrote about *an ethical engineer* at the beginning of the course compared to the end of the course.

4.4 Naïve Bayes Results

In order to carry out an analysis using naïve Bayesian methods to discriminate beginning vs end of course essays, a Bayesian classifier was trained on a random half of the pre and post essays and was then tested on the remaining essays. In the training phase, the classifier learned the discriminating concepts that distinguished beginning-of-course essays from end-of-course essays. In the test phase, the classifier predicted whether an essay was from the beginning of the course or the end of the course. Results are summarized in Table 2.

The table shows that of the 24 end-of-course essays, Bayes correctly classified 24 and misclassified 25. Of the beginning-of-course essays, Bayes correctly classified 29 and misclassified 20. The results show that the classifier had a 55% accuracy rate in classifying new essays as originating in the beginning of the course versus the end of the course. The absence of strong differentiation effects is consistent with the LIWC analysis, which also failed to find differences between beginning and end of semester essays.

Table 2. Confusion Matrix Showing Frequencies (Percents in Parentheses) for Classification of 49 New Beginning of Course Essays and 49 New End of Course Essays Using a Naïve Bayes Classifier

Naïve Bayes Results			
Predicted	**Actual**		
	End of Course	Beginning of Course	Row Total
End of Course	24 (.25)	20 (.20)	44
Beginning of Course	25 (.26)	29 (.30)	54
Column Total	49	49	98

To further analyze the results summarized in Table 2, we proceeded as follows. Naïve Bayes provides for the extraction of the Bayesian conditional probabilities associated with individual predictors. Combining this output with the *a priori* probabilities of pre-essays and post-essays in the training trials, it is easy to compute the Bayesian probabilities for each of the predictors in the corpus. Knowledge of the strongest predictors can then be fed back into students' essays as markup, in order to make more explicit the conceptual structure and organization within the essays. The output from the first step in this more detailed analysis of the essays is shown in Table 3, which shows the rank ordered predictors (reduced to word stems), which the naïve Bayes algorithm used to classify essays as a beginning vs end of course essay. A visual analysis of the differences between Table 3A and 3B suggests more emphasis in the end-of-course stems on concepts like NSPE code, contract, faith, etc.

Table 3. Rank-Ordered Word Stems that Discriminate Beginning vs End of Course Essays

A. Rank-Ordered Stems Predicting Beginning-of-Course Essays
credibl, achiev, main, natur, plant, deadline, manufactur, million, procedur, energy, popular, lose, around, materi, charact, save, describe, increase, key, member, office, structur, third, topic, view, due, surround, team, address, calcul, circumst, complet, conclus, confid, fall, fellow, mindset, observ, occur, research, solut, system, thought, trust, year, valu, accur, plan, everyon, present, regul, meet, say, might, product, want, deal, decid, friend, kind, lower, necessari, path, privat, qualiti, quit, relationship, risk, social, student, wast, concern, instead, often, rather, said, sound, chang, daili, demonstr, happen, measur, stand, top, word, case, correct, see, success, live, effect, prioriti, appli, environment, moreov, produc, reliabl, sens, test, toward.

B. Rank-Ordered Stems Predicting End-of-Course Essays
nspe, industri, privaci,breach, serious,civil, dont, publics, faith, accord, colleagu, document, engag, abid, forward, parti, attempt, found, overn, open, sever, paramount, financi, nation, welfar, uphold, reput, agenc, benefici, anon, contract, exagger, extrem, favor, legal, maxim, name, offer, offici, realiz, releas, shall, stop, desir, loyal, play, direct, author, knowledg, law, break, data, detail, falsifi, mention, method, mistak, preserv, titl, train, truth, feel, highest, stay, trustworthi, amount, commit, decept, leav, sign, compet, involv, area, negat, continu, learn, servic, communiti, day, influenc, major, qualifi, reason, done, report, code, protect, hold, issu, along, capabl, conflict, corrupt, demand, grow, hire, oss, mechan, mental, move.

In order to visualize the impact of the predictors on classification, we chose two post-course essays: one that was classified by naïve Bayes as a highly probable post-course essay and one that was classified as a low probable post-course essay. The Bayesian predictors from Table 3B are bolded in the essays. The high-probable post-course essay in Table 4A clearly shows numerous words (concepts) predictive of a post essay compared to the low-probable post essay in Table 4B. The predictors in the high-probable essay are exactly the kinds of concepts that we would expect to emerge in a course that emphasized ethical principles and ethical behavior, and the NSPE code of ethics for engineers. The contrast depicted in Table 4A vs 4B suggests there may be significant individual differences in the extent to which students change their ethical thinking as a result of participation in the course. Further analysis of individual differences will be undertaken in ongoing work.

5.0 Discussion

This study describes preliminary steps in utilizing machine methods to extract the conceptual basis in students' ethics essays. The weak results in both analyses suggest that there is no discernable difference in students' conceptualization of an ethical engineer from the beginning of the course to the end of the course. Both LIWC and naïve Bayes allow for examination of the predictors used to classify essays, which will allow a better understanding of the weak results. First steps to better understand individual differences in the present data are depicted in Table 4.

If subsequent evidence from the present analyses suggests that Bayesian analyses can readily extract reliable predictors from student-generated samples, several potential benefits emerge for instructors: 1) content analysis can be tailored to students' vocabulary levels, regional vernacular, and other word choice factors; 2) the possibility of a flexible range of analysis, i.e., it would afford the analysis of short responses or longer essays; and 3) focus on course-related subject matter, i.e., classifiers could be directed to specific course topics. These would be significant aids in analyzing students' conceptual understanding and developmental progress as the result of instruction. Further development and testing of methods will better indicate the instructional prospects for these machine methods.

Table 4. Two Sample Essays with Bayesian Predictors Highlighted

A. High Probable Post-Course Essay According to Naïve Bayes Prediction
Since engineering is the forefront of modern innovation and drives most economies in the world, professional engineers are expected to **uphold** various ideals in order to ensure the publics well being. Things like sexual harassment, political **corruption**, money laundering, falsifying **data**, and all sorts of other things have poisoned the engineering world. In this paper I will outline some of the things that are expected of a professional engineer in a modern society. All engineers are expected to contribute to society in a positive way. This means that we are to create products and **services** that aren't detrimental to the public good. Engineers shouldn't **commit** acts ofsexual aggression in the workplace without consent. This is still a problem for some **reason** so some companies have removed the restriction of not being allowed to date a coworker to not confuse the presence of hook up culture and sexual harassment in court. Engineers are to be honest except when it comes to revealing company secrets. This has been a grey **area** for a while now, but essentially it means you are expected to tell the **truth** about a **service** or product as long as it is information deemed suitable for the public. Engineers must **protect** the privacy of others. With **data** being one of the world's most valuable resources, **data** on anyone and everyone is always readily availableso we must **protect** it at all costs. And lastly, engineers must follow established **laws**. If engineering companies step outside of what is allowed under the **government** the consequences can be detrimental to both the public and the company itself. There are many more concepts not outlined in this paper an engineer must **abide** by. The **NSPE Code** of Ethics, IEEE **Code** ofEthics, and ACM **Code** of Ethics all outline some of those topics as well as topics that are specific to different **industries**. These expectations also **hold** for students and anyone else that is **involved** with the engineeringworld. Since the development of these **Code** of Ethics, more schools have adopted and required ethical courses as a countermeasure for unethical decisions made in the workplace and for that I think the future looks a little brighter.
B. Low Probable Post-Course Essay According to Naïve Bayes Prediction
It is not surprising that engineering is one of the most trusted professions in America. Engineers are responsible for a myriad of responsibilities within a country. They are responsible for maintaining the country's energy grid, constructing new roads and highways for public transportation, and creating software that can help the average American with their daily lives. To maintain the positive opinion Americans has toward engineers, graduates entering the field must be held to a high degree of ethics. An ethical engineer must **hold** the American people's safety to a high regard. As previously stated, engineers are responsible for many things that make America function. Due to this fact, whatever an engineer does can affect millions of Americans. An ethical engineer needs to make sure that it does not harm the health of the people. For example, an oil company needsto make sure that all functions within the facility are adhering to federal safety regulations. If not, then the facility could create another BP oil spill situation, where lives are lost, and the oil spill could affect the drinking water of millions of Americans, thus endangering their health. It is understood that an ethical engineer needs to know what he/she is doing during their job. A recently graduated college student should know the responsibilities their job entails and make a logical conclusion as to whether they should accept the job or not. If a recent graduate were to accept a job despite not fully understanding how to do their job, it could not only slow down a company's **growth** but also cause the company to perform at its best, which could compromise the safety of many Americans. Lastly, an ethical engineer needs to make sure that it acts with honor. They should not result to shady business dealings that could compromise the **reputation** of the company. For example, an ethical engineer should not accept **financial** contribution from a political figure in the hopes of trying to **influence** the engineer. This in turn will create a **conflict** of interest within the company, with the public claiming that the company values monetary gain over their lives.

Note. Bayesian predictors are highlighted.

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