Developing Machine-Assisted Analysis of Engineering Students’ Ethics Course Assignments

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.

Mr. Mark Stephen LaCour Jr., Texas Tech University

Mark is a doctoral student in the Department of Psychological Sciences at Texas Tech University. He completed his thesis on the role of calculator usage on mathematical cognition at the University of Louisiana at Lafayette.

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. Richard A. Burgess II, Texas Tech University

Richard Burgess currently works as an Instructor in the Murdough Center for Engineering Professionalism (MCEP) and National Institute for Engineering Ethics (NIEE) in the Whitacre College of Engineering at Texas Tech University. He oversees the day to day operations of the Center’s distance learning courses for both engineering students and practicing engineers. Additionally, he teaches an on-campus ethics course for undergraduate students. Burgess provides guest lectures on ethics throughout the Whitacre College of Engineering. Burgess has also worked to incorporate ethics into K-12 STEM education. The push to increase the number of students pursuing STEM careers needs to be accompanied by a sophisticated understanding of the complexity of technology. Ethics is a key part of this complexity and the next generation of STEM professionals will need the skills to effectively engage the ethical challenges they will face. Burgess is a regular presenter on incorporating ethics in a K-12 setting. A theme throughout these roles is the importance of teaching ethics and promoting ethical reflection in a way that is both accessible and substantive. This is a challenge that Burgess is keenly interested in. He holds bachelor’s and master’s degrees in Philosophy and is currently a PhD student in Systems and Engineering Management program in the Texas Tech Industrial Engineering Department.
Developing Machine-Assisted Analysis of Engineering Students’ Ethics Course Assignments

Abstract

Our research concerns engineering ethics education. We were drawn to this topic by a recent paper titled “Do Ethics Classes Teach Ethics?”, but more so by ABET criteria 3f and 3h regarding the development of ethical responsibility in engineering students. The purpose of the present project is to use the learning and analytical capabilities of IBM Watson Natural Language Classifier to analyze capstone papers submitted by undergraduates in a course on engineering ethics. The capstone papers that we analyzed required students to identify and discuss a contemporary engineering technology (e.g., autonomous tractor trailers) and to explicitly discuss the ethical issues involved. In the two tests described here we assessed whether Watson-NLC could classify sentences from students’ papers as either related to ethics or not related to ethics. Additionally, we consider the utility of these simple machine-based classifications. Our longer-term goals are to use Watson-NLC to identify the ethical theory or theories from the course that students adopt to frame their ethical positions, to assess the effectiveness of students’ ethical arguments, and to assess changes in ethical thinking across the semester.

Introduction

Advances in science and engineering inevitably raise ethical issues. For instance, should we build an offshore oil platform if it would reduce dependence on foreign oil but is a threat to the ecosystem? What new hazards for people do self-driving cars and trucks create, and who should assume liability if the technology fails? Should we promote computer hacking if it is subversive but increases national security? In our work with students in an undergraduate engineering ethics course, we have found that ethical issues and questions like these deeply engage students. It would be beneficial to students and consistent with the mission of engineering education to develop this enthusiasm into rigorous and informed ethical reflection. In this project we explore how an intelligent machine, specifically, IBM Watson Natural Language Classifier (Watson-NLC), can assist in this work.

Ethics is a fundamental topic in engineering education [1] that is consistent with ABET goals for engineering students: 3f. An understanding of professional and ethical responsibility; 3h. The broad education necessary to understand the impact of engineering solutions in a global, economic, environmental, and societal context. Teaching ethics in engineering is obligatorily different than teaching a technical engineering topic, like statics. Whereas the latter involves fixed constants, physical principles, and solving equations, ethics is more verbal, involving discussion and essay forms of interaction. Students may be required to participate in online discussions, post to blogs, and submit research papers. With large class sizes, instructor workload could become substantial. The pedagogical goal of the present project is to develop the means to better prepare engineering students for professional careers in which they exercise ethical judgement in their technical work and are cognizant of the impact of their decisions on individuals, the community, and beyond. The research goal is to develop ways in which machine-assisted analysis of students’ written compositions in ethics courses can serve as an
The context of our research is a sophomore-level course that is offered to engineering majors at our university. This course develops ethical reasoning 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, and virtue ethics – and the National Society of Professional Engineers Code of Ethics. Course activities require students to analyze and respond to ethical issues in contemporary social settings involving engineering dilemmas. A major course requirement is a capstone paper incorporating Social Impact Analysis (SIA). The general purpose of SIA is to identify and analyze the positive and negative social consequences of engineering plans and projects. In students’ SIA papers, they identify and discuss a contemporary engineering technology (e.g., autonomous tractor trailers, fracking, drones, ethical hacking). They are required to incorporate knowledge from one or more of the ethical theories into their analyses.

The goal of the present study was to use machine-learning to identify the ethical content in the capstone papers submitted by students in the ethics course. In the two tests described in this paper, we assessed whether Watson-NLC could classify sentences from students’ papers as either related to ethics or not related to ethics. Further, we consider the utility of these simple machine-based classifications. Our longer-term goals are to use Watson-NLC to identify the ethical theory or theories from the course that students adopt to frame their ethical positions, to assess the effectiveness of students’ ethical arguments, and to assess changes in ethical thinking across the semester.

Machine Learning and Text Analysis

Machine analysis of text is not a new idea. An influential model related to the analysis of the semantic content in texts is Latent Semantic Analysis (LSA) http://lsa.colorado.edu/. LSA uses a sparse matrix of correlations between words and documents in order to represent the interrelationships of concepts within a high-dimensional semantic space. These correlations reliably correlate with human judgments of similarity, or relatedness, of meaning. One limitation of LSA is its approach to structured language – e.g., a sentence – as a “bag of words.” Thus the model is constrained by its inability to capture the logical, syntactic structure of language, which relates to meaning. For instance, in the sentence, “The dog chased the cat,” the syntactic structure of the sentence will determine who is doing the chasing and who is being chased.

Another software application, called CohMetrix http://cohmetrix.com/, provides measures of the properties of a text. These properties include the coherence of text, its readability level, and its syntactic complexity. CohMetrix provides measures of the coherence of mental representations that are based on a text, but not the semantic content of those representations.

IBM Watson – Natural Language Classifier

The machine-learning system that we are testing is the IBM Watson Natural Language Classifier (Watson-NLC). IBM has developed a suite of intelligent tools within the IBM Watson program.
One of these, the Natural Language Classifier, is based on deep learning, which currently applies the most powerful learning algorithms for intelligent machines [http://www.ibm.com/watson/developercloud/nl-classifier.html](http://www.ibm.com/watson/developercloud/nl-classifier.html). The Natural Language Classifier can be trained to classify information in any domain. Examples from the IBM website include:

- Classify SMS texts as personal, work, or promotional
- Classify tweets into a set of classes, such as events, news, or opinions
- Tackle common questions from your users that are typically handled by a live agent
- Trigger actions in an application, such as start another application, respond with an answer, or begin a dialog

In our application, Watson-NLC learns how words and phrases from students’ essays relate to specific classifications. With sufficient training Watson-NLC can readily classify new instances.

Training Watson-NLC is straightforward. The input file to Watson-NLC is a .csv (comma-separated values) file consisting of two columns and multiple rows. Each row constitutes a training instance. The first column in any given row contains an instance of a classification. The second column in a row contains the classification for the instance. The classifications for each training instance are determined by human raters. An example of a .csv file for training Watson-NLC is shown in Table 1.

<table>
<thead>
<tr>
<th>Example Input Sentences From Student Paper</th>
<th>Classifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>The fact that the United States was able to have large economic gains due to fracking made this a very viable route to phasing out coal power which is still very widely in use throughout the world.</td>
<td>Not Ethics</td>
</tr>
<tr>
<td>It is seen as a potential way to continue the growth in economy and electricity generation to eventually switch over to renewable resources, but for the time being has proven to not only be economically viable, but allowed the United States to gain influence over other countries who continue to develop and need new energy sources.</td>
<td>Not Ethics</td>
</tr>
<tr>
<td>Despite large benefits there have also been drawbacks.</td>
<td>Not Ethics</td>
</tr>
<tr>
<td>Possibly the largest concern about the use of fracking would be the effect it has on our fresh water supply; both contaminating it with chemicals creating more toxic water than water treatment plants can handle, and contaminating local water supplies.</td>
<td>Ethics</td>
</tr>
<tr>
<td>Since water is the main fluid being used in the process, this totals up to very large amounts of water being rendered unusable for drinking or farming.</td>
<td>Ethics</td>
</tr>
</tbody>
</table>

The .csv training file is submitted to Watson-NLC, which builds a classifier based on the instances provided to it. Figure 1 gives a sense of the Watson-NLC user interface.

After the classifier is built, it can be used to classify new instances. The output that Watson-NLC provides for old and new instances looks very much like a .csv input file. The difference is that the output includes an additional column, which shows Watson’s classifications for each
Figure 1. The Watson-NLC User Interface.

Figure 2 shows a sample of test outcomes. Column B shows the experimenters’ original assignments and Column C shows the Watson-NLC assignments and confidence in those assignments.

Figure 2. Portion of a Watson-NLC Output File

Tests of Learning in Watson-NLC

In this section we report two tests in which we trained Watson-NLC to classify ethical elements in students’ SIA papers. In these tests, we trained Watson-NLC to simply classify the sentences in students’ SIA papers into two categories: Ethics and Not Ethics, as suggested by Figure 2. The goal of these tests was to assess whether Watson-NLC could make these classifications, and whether Watson’s agreement with human raters would improve with additional training.

For the first test, we chose ten SIA capstone papers at
random from the corpus of archived course papers. One of the researchers classified each sentence in the papers as ethics or not-ethics. A second researcher verified these classifications. In cases of disagreement between researchers, a final classification was determined through discussion and consensus. The final classifications were used to build a classifier with two categories: ethics and not-ethics. Ten new SIA papers were then used to test the classifier.

The classification results for ten new papers that Watson-NLC had not seen previously are shown in Table 2. Across the ten new papers, the average agreement of Watson-NLC with the human raters was 74.60%. Watson-NLC is clearly performing better than chance, but not in perfect agreement with the human classifiers. Given that the classifier was trained on only ten example papers, the results appeared quite promising.

Table 2. Watson-NLC Classifications of Sentences in Ten New SIA Capstone Papers into Ethics and Not-Ethics Categories After Training on Ten SIA Papers

<table>
<thead>
<tr>
<th>Student Paper</th>
<th>Sentences Agreed</th>
<th>Sentences Disagreed</th>
<th>Total Sentences</th>
<th>Percent Agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td>S11</td>
<td>97</td>
<td>24</td>
<td>121</td>
<td>80.17</td>
</tr>
<tr>
<td>S12</td>
<td>102</td>
<td>16</td>
<td>118</td>
<td>86.44</td>
</tr>
<tr>
<td>S13</td>
<td>42</td>
<td>10</td>
<td>52</td>
<td>80.77</td>
</tr>
<tr>
<td>S14</td>
<td>80</td>
<td>27</td>
<td>107</td>
<td>74.77</td>
</tr>
<tr>
<td>S15</td>
<td>43</td>
<td>23</td>
<td>66</td>
<td>65.15</td>
</tr>
<tr>
<td>S16</td>
<td>66</td>
<td>23</td>
<td>89</td>
<td>74.16</td>
</tr>
<tr>
<td>S17</td>
<td>64</td>
<td>35</td>
<td>99</td>
<td>64.65</td>
</tr>
<tr>
<td>S18</td>
<td>58</td>
<td>27</td>
<td>85</td>
<td>68.24</td>
</tr>
<tr>
<td>S19</td>
<td>59</td>
<td>19</td>
<td>78</td>
<td>75.64</td>
</tr>
<tr>
<td>S20</td>
<td>73</td>
<td>23</td>
<td>96</td>
<td>76.04</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>68.40</strong></td>
<td><strong>22.70</strong></td>
<td><strong>91.10</strong></td>
<td><strong>74.60</strong></td>
</tr>
<tr>
<td><strong>SD</strong></td>
<td><strong>20.18</strong></td>
<td><strong>6.75</strong></td>
<td><strong>21.93</strong></td>
<td><strong>7.00</strong></td>
</tr>
</tbody>
</table>

In order to test if the level of agreement between Watson-NLC and the human raters could be improved, an additional 30 papers were presented to Watson-NLC for training. After building a classifier from these 40 papers, Watson-NLC was tested on ten new papers. Average classification agreement of Watson-NLC with human raters increased to 79.30%. Detailed results are shown in Table 3.

Table 3. Watson-NLC Classifications of Sentences in Ten New SIA Capstone Papers into Ethics and Not-Ethics Categories After Training on Forty SIA Papers

<table>
<thead>
<tr>
<th>Student Paper</th>
<th>Sentences Agreed</th>
<th>Sentences Disagreed</th>
<th>Total Sentences</th>
<th>Percent Agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td>s60</td>
<td>63</td>
<td>11</td>
<td>74</td>
<td>85.14</td>
</tr>
<tr>
<td>s61</td>
<td>103</td>
<td>20</td>
<td>123</td>
<td>83.74</td>
</tr>
<tr>
<td>s62</td>
<td>66</td>
<td>17</td>
<td>83</td>
<td>79.52</td>
</tr>
</tbody>
</table>
The trend of increased agreement with additional training is depicted in Figure 3. As Watson-NLC gains more experience with the classification task, agreement with human raters increases and disagreement decreases.

**Figure 3.** Watson-NLC Percent Agreement and Disagreement with Human Classifiers, by Training Input

Potential Applications

These early results suggest several classroom applications. Figure 4 shows one student’s complete paper that has been reduced in size to illustrate two properties. Sentences related to ethics are highlighted in green. A visual scan suggests only scant consideration of ethics in this paper, and a scattered distribution of ideas related to ethics.

If the output from Watson-NLC could be converted into a visual representation similar to that shown in the figure, it would have utility for the student and instructor as a rough indicator of whether the student fulfilled the SIA paper requirement to provide substantial discussion of ethical issues. Further, the proportion of the paper dealing with ethics could be easily calculated. Either form of output would provide the instructor with leverage in prompting students to further develop a position regarding the ethical issues associated with the engineering topic of the paper.
Solar Panels: our clean and safe option for the future.

The sun is a natural and free source of energy. Also, it is silent and pollution free. Solar energy has a lot of potential and many advantages that with time, it might replace other resources of energy such as fossil fuels. Accordingly, to National Geographic, every hour of energy that the sun beams onto earth can give enough energy for the planet need for an entire year. Nowadays, solar energy technology produces less than 2% of the world energy, but its implementation is growing exponentially.

Solar panels have been around us for quite a while and we might not even notice. For instance, many scientific calculators, stop lights, wallcharts, rooftops, and every everyday electronic devices contain this technology already. However, these devices have not been in use. In addition, there are solar panels that are up to 48% efficient compared to the common solar panels which have an average of 16% efficiency. These efficient solar panels are expensive and not convenient to generate profit.

Accordingly, to energy matters, the person that discovered the photovoltaic effect is Alexandre Edmond Becquerel, he claimed that electricity could be produced out of the sun energy that radiates into or planet in 1839. Moreover, it was too early for the implementation of photovoltaics cells at that time and the levels of efficiency where incredibly low. Consequently, more than 100 years later, using the same principle that Becquerel had discovered, but with the technology advancements at the time, he invented the solar cell. The basics of how a photovoltaic cell works consists of light striking certain element or compounds, which will cause the material and its surface to emit more electrons. The combination of these reactions make electrons flow possible and therefore allow electricity to happen.

Solar energy implemented in solar panels have advantages and disadvantages like any other form of energy as shown below.

**Benefits of Solar energy:**
- Sustainable
- Flexible
- Environmentally friendly
- Fast improvement
- "Noise free"
- Decrease of cost
- Improved health
- Low maintenance

**Drawbacks of solar energy:**
- Hard to install
- Little pollution to manufacture
- Needs large space (land)
- Less efficient at high altitudes
- Dependent on the weather

We do not want to attach more importance to this suggestion than it deserves, but rather to indicate that the machine resource has instructional utility even at this simple level of analysis.

---

**Types of Solar Energy**

- Most panels are made of silicon, which is the third most common element on earth, behind iron and oxygen. This panels made of silicon are divided into two categories, monocrystalline and polycrystalline. Monocrystalline solar panels are traditionally more expensive and they are usually long cylinder-shaped. Polycrystalline panels have usually a blue color and are formed of molten silicon. This panels are more efficient and more common nowadays.
- Micro inverters are not a type of solar panel, but an implementation that made the panels more solar efficient. These inverters transform Direct current (DC) to Alternating Current (AC). Before micro inverters, if there was any disturbance in the solar panels, their efficiency will drop tremendously. But with the implementation of microinverters those problems are no longer existent and the solar panels can control the excess energy from the inverters.
- Solar troughs are cylindrical throughs that used their energy at a tube in the middle that contains a liquid that warms up to heat water as a heat exchanger. The other technology used (Solar Troughs) are large towers with mirrors around which heat the water around it to boil it. Usually, solar troughs are still very expensive and are used in companies that need to boil water for industry purposes.
- Solar towers are tubes that contain water inside and that will desalinate the water using the same principle that Bacquerel discovered, but with the technology advancements at the time, he invented the solar cell. The basics of how a photovoltaic cell works consists of light striking certain element or compounds, which will cause the material and its surface to emit more electrons. The combination of these reactions make electrons flow possible and therefore allow electricity to happen.
- Solar energy implemented in solar panels have advantages and disadvantages like any other form of energy as shown below.

**References**


systematically first presents the technical aspects of the engineering topic and then brings in and develops the ethical concerns. Watson-NLC could be used to automatically provide a sense of organization and feedback to the student, based on the distribution of ethical and non-ethical content.

**Future Directions**

Our current classifier can be thought of as a Stage 1 classifier that separates ethics-related content from technical descriptions. Going forward, we intend to develop a Stage 2 classifier that will classify the ethics-related statements in the SIA papers into the several theories that are covered in the course – i.e., *utilitarianism, respect for persons, and virtue ethics* - as well as the NSPE code and *intuitionism*, which is the view that ethical issues and moral judgments are immediately apprehended. These classifications would be informative to instructors, in part, by indicating the extent to which students internalized the ethics of the course. Specifically, these machine classifications would provide useful data regarding the question of which ethical approaches were internalized. These data would give instructors feedback on where changes might be made in the course.

The current available data include only the capstone SIA papers. However, in future work we hope to also assess changes in ethical thinking from early to late in the course through the analysis of early and late student compositions. It is possible that the gains are small. Such an occurrence would be consistent with Haidt’s [3] pessimistic view that so-called moral reasoning is really an epiphenomenon—they are simply one’s post hoc rationalizations for what are ultimately moral intuitions—i.e. instances of ethical *intuitionism*. More optimistically, assessments of changes in ethical reasoning could help identify students who had not adequately internalized the course content and who could benefit from additional development.

**Conclusions**

The theoretical question of man vs machine has some merit and interest. More importantly, though, developing the means of using machine systems to assist in course assessments would allow instructors to provide more extensive and incisive feedback and guidance in ethics courses, by complementing their assessments of students’ work. This is a timely issue in any course, like engineering ethics, with high enrollments, that entails substantial student writing, and that requires considerable instructor time for scoring. We regard exploring these complementary assessment approaches as potentially having a high payoff in engineering ethics education and assessment.

There is clearly a cost-benefit issue in attempting to train machine classifiers to carry out assessments in specialized courses. The difficulty of assessing ethical content in SIA papers is compounded by the fact that the course and papers involve multiple ethical theories and ethical codes and approaches. Clearly, building a classifier for a course that is offered only infrequently and that has low enrollments would produce a high cost to benefit ratio.

A recent paper titled “Do Ethics Classes Teach Ethics?” [4] raises pertinent questions for engineering ethics education, questions about what is gained and how much change takes place
through coursework. Machine-assisted assessments of the sort described here could provide some insight into this question.

References


