Machine-Assisted Analysis of Communication in Environmental Engineering

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Abstract

ABET is committed to promoting the broad development of engineering students, including knowledge of the social, cultural, environmental, and global implications of engineering practice. Coincident with the cultural shift within engineering education is a scholarly interest in the formal and informal communications of engineers and students. The present study was situated in a graduate course in environmental engineering that incorporated the arts and humanities with the goal of developing personal and professional reflection in students. The goal of this paper is to describe and analyze two methods of machine-based formative assessment of students' essays written in response to lectures and activities that related to art and narrative within the course. The two machine-based tools used here were i) naïve Bayes analysis and ii) Meaning Extraction Helper. The results showed that both tools were able to identify differences in student essays. We suggest several ways in which these machine-based methods could be extended to aid in assessing learning and reflective thinking in students.

Introduction

In U.S. engineering education, ABET (Accreditation Board for Engineering and Technology) advocates the broad development of engineering students.[1] Congruent with ABET guidelines, engineering researchers have framed principled foundations for understanding engineering practice in social, cultural, environmental, and global settings [1]-[4]. Concurrently, engineering educators have made a call for transformational change in engineering education [5]. Presently, engineering education is entrusted with incorporating a full range of social, cultural, environmental, and global considerations that may be involved in professional engineering practices.

A scholarly interest in engineering communication has emerged as part of the broadening of engineering education and practice to acknowledge and respond to issues that extend outside of technical knowledge [6]. ABET has included communication in Criterion 3 competencies as "an ability to communicate effectively with a range of audiences"[1]. Engineering communication is often thought of as being "purely technical and neutral" [6]; however, this is considered by Leydens [6] to be a myth. A sense of the breadth and richness of engineering communication in present day engineering education is evident in the work of Loshbaugh and Claar [7] whose data include conversations, structured and semi-structured interviews, and surveys. Broadening the scope of the development of engineering students is currently achieved, in part, through the discussion and written reactions to engineering case studies [8] [9] that reflect the types of situations students are likely to encounter in professional practice. Engineering communication also applies in areas like design [10] and others.

A growing interest in the engineering education community is in discovering ways in which the professional preparation of engineers can be strengthened and enriched by incorporating

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[1] https://www.abet.org/accreditation/accreditation-criteria/criteria-for-accrediting-engineering-programs-2019-2020/#GC3

perspectives and skills from the arts and humanities [11] [12]. The present study describes a subset of activities and analyses from a graduate course in environmental engineering supported through the NSF Innovations in Graduate Education (IGE) program. The goal of this paper is to describe and analyze two methods of assessing the content of students' written submissions in this graduate course using machine-assisted text-analytic methods.

Methodologically, the analyses in this paper apply text-analytic procedures to qualitative data. The purpose of text analytics is to draw meaning out of written communication, typically, with a pragmatic goal. The purpose of the present project was to apply and test two text analytic tools: i) naïve Bayes analysis and ii) Meaning Extraction Helper (MEH). These methods can be applied to transcribed verbal interactions from discussion groups or to written work. The present paper focuses on the latter type of data—i.e. brief open-ended essay reaction papers—with an ultimate goal of implementing formative assessments and automated feedback to students.

Theoretical Basis for the Present Study

The theoretical foundation for this study comes from the work of Pennebaker and King [13] who proposed that "the way people talk about things reveals important information about them" (p. 1297). According to this thinking, Pennebaker et al. [14] reasoned that it should be possible to construct lists of words that identify specific "beliefs, fears, thinking patterns, social relationships, and personalities" (p. 1) that characterize individuals based on the words that they use. In order to test this thesis, Pennebaker and colleagues [14] developed Linguistic Inquiry and Word Count (LIWC)[2], which is a machine tool used to analyze the semantic content of documents, like essays, editorials, novels, and blog comments. LIWC is based on the analytic assumption that aspects of the semantic content of text can be reliably recovered through algorithmic methods. LIWC works by searching for terms that appear in pre-selected word lists that represent both broad categories—like *positive emotion, cognition,* and *biological processes*—and specific categories—like *anger, sad, family, and health*. The applications of LIWC have been broad, with implementations in clinical [15] [16], academic [17]-[19], and financial [20] domains, among others.

Pre-defined categories based on word lists can be useful in some settings, as demonstrated by the success of LIWC. However, an instructor in the classroom typically faces a need for more specific analyses than those afforded by analytic tools like LIWC. Instructors generally want to know if students are learning as a consequence of instruction, and the specific knowledge that students gain. Whereas LIWC can be described as implementing a *top-down* approach to analysis—i.e., an approach in which the categories of interest are known and defined in advance of the application to data—machine methods offer alternative *bottom-up* approaches—i.e., analyses in which the data are used to define the relevant categories. Both top-down and bottom-up methods rest on a fundamental computational principle that underpins a wide-range of intelligent machine-based systems, including the two that are examined here. The principle simply stated is that *There are highly probable markers (cues, features) in the input (e.g.,*

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[2] http://liwc.wpengine.com/

student essays) that characterize key constructs in the input. Therefore, in principle, it should be possible to identify and use these cues in applied settings, like a classroom.

The Instructional Context of the Present Study

Through support of an NSF Innovations in Graduate Education (IGE) grant, we developed a graduate course in environmental engineering that aims to promote reflective practices in engineering students. The present analyses focus on two teaching modules from the course that have an overall theme of *Engineering, the Environment, and the Community*. The goal of the first module, *Art*, was to present the work of artists and their reflections on creativity in order to promote reflective thinking in the students about how art and creativity might relate to engineering practice. The goal of the second module, *Narrative*, was to encourage reflective thinking in the students about the ways in which formal and informal narratives communicate information about engineering and affect the public's perception of engineering practices and achievements. These two goals were carried out in five one-hour lessons that were led by guest instructors with specializations in cognitive psychology, the psychology of art, and narrative and media communication.

The first three lessons (*Art 1, 2, & 3*) concerned the role of artistic creativity in engineering. Creativity involves seeing things we think we know in a different way, taking risks, and exercising curiosity. During these lectures and discussions, students were asked to consider questions of what is artistic, beautiful, creative, chaotic, radical, emboldening, and restorative in engineering. Engineering and its products inevitably enter into narratives. The next two lessons (*Narrative 1 & 2*) concerned the ways in which formal and informal narratives of engineering define the perceived values of engineering products and practices. The class discussed how personal and cultural values are embedded in the narratives we use to communicate, and how these narratives shape the ways that engineering is viewed in communities that it affects.

The five lessons were anchored by a common theme, which was repeated in each lesson: What is the relation between an engineer, the environment, and a community? The same homework assignment followed each lesson. For each assignment, students composed and submitted a brief essay. The instructions were as follows:

> *How do you currently conceptualize (deeply understand) the relationship between an engineer, the environment, and a community? Respond in an open-ended essay (500 words) organized into paragraphs. Include a References subsection at the end for published sources that you draw from and cite, in order to give proper acknowledgment of your sources.*

Pedagogically, the purpose of maintaining a common theme and exercise was to prompt students toward deeper consideration of this relationship. From a research perspective, the purpose of administering the same homework assignment was to keep the target question constant and to monitor changes in students' responses to that question.

Overview of Methods of Machine-Assisted Assessment Applied in this Study

The present applications of machine-assisted methods relate to the formative assessment of students—i.e., assessment *for* learning[3]. The methods are descriptive and meant to inform the instructor of students' understanding of the material and development of their thinking. Common methods of assessment for learning include portfolios, teacher observation, and conversation with students. The two machine-assisted methods applied here, naïve Bayes and Meaning Extraction Helper, were tested for their capacity to provide informative descriptive data regarding student learning. Naïve Bayes was put to a more rigorous test of being able to accurately assess new cases, as described in more detail below.

Naïve Bayes is an algorithm based on the calculation of conditional probabilities. The algorithm can be used to build classifiers using supervised learning methods. Basically, instances of interest are classified into categories and then separated into training and test sets. Prior to analysis, a naïve Bayes classifier first eliminates function words (like *the, a, if, on*) and punctuations, and simplifies content words by retaining word stems and eliminating word endings (i.e., a process of stemming). The classifier then computes the strongest predictors within those instances, using the stems in the essays, in order to best match the assigned classifications, and can then apply these predictors to new instances

Meaning Extraction Helper (MEH) [21] is a software package related to Chung and Pennebaker's "meaning extraction method" [22]. MEH carries out a number of relevant functions related to text analysis, like calculating individual word frequencies in the texts. Similar to naïve Bayes, MEH eliminates function words and punctuations prior to analysis, but in contrast to naïve Bayes, MEH does not apply stemming, but rather uses lemmatization. Lemmatization tends to produce more easily interpretable predictors because they generally correspond to root words.

Naïve Bayes and MEH Procedures

The data for the present analyses consisted of the essays that students submitted for their homework assignment following each lesson (described earlier). There were nine students in the course and each student submitted five essays (i.e., one essay per week) for a total of 45 data points. In the present case, for classification by naïve Bayes, the student essays were simply separated into the week of completion. Naïve Bayes generated two sets of data:

i) accuracy data for classifying new essays after training on a subset of essays, and
ii) the predictors (word stems) that naïve Bayes used to make the classifications.

The logic underlying the Bayes procedure was as follows. The overall goal was to assess change in students' thinking. We assumed that an effective lesson would communicate and evoke a detectible change in students' formulation of the relationship between engineer, environment, and community, which was the central theme of the lessons and which was probed in each of the five homework assignments. Under this logic, the algorithm would be able to discriminate/predict differences between student submissions from week to week. An inability of the algorithm to reliably discriminate differences would suggest dispersed (scattered) thinking across students and, in some sense, a failure of instruction to deliver an effective and distinct learning experience from one week to the next.

[3] https://www.teachthought.com/pedagogy/the-difference-between-assessment-of-learning-and-assessment-for-learning/

Naïve Bayes was implemented in R through R-Studio, using package e1071 and Laplace smoothing.[4] Numbers, stop words (e.g., function words like *the*, *if*, *on*), which carry little lexical meaning in a document, and punctuations were removed, and stemming (e.g., reducing *trouble, troubles*, *troubling* to *troubl*) was applied. These are typical steps in applying naïve Bayes methods. The modification of the data, as described, resulted in approximately 340 word stems across the 45 essays. The naïve Bayes analysis was based on these predictors. Because of the small data sample, leave-one-out cross-validation (LOOCV) was applied. Basically, the algorithm trained on 40 essays (eight students *times* five weeks) and tested on the one student (five essays) that was left out, until the algorithm had rotated through the nine students and had tested each one of them.

In the present application, MEH was used to identify the most frequent terms used in the same texts that were analyzed using the naïve Bayes procedure. Word frequency gives one indication of the centrality of specific, high-frequency concepts in an essay. The predictors computed using naïve Bayes (see item ii above) are based on the Bayesian probability for the predictor. Therefore, MEH provided another lens through which to examine the most significant predictors in the essays. MEH was implemented through application of the standard MEH software package [21].

Naïve Bayes Results

The first set of results for naïve Bayes was derived from the training and testing data. As an initial exploratory step in the data analysis, naïve Bayes was trained on all the data (45 essays) and required to classify the week in which the essay was written (Week 1-5). The algorithm achieved 100% accuracy. This indicated that there was a sufficient number of reliable predictors for discriminating changes in students' responses across the five weeks for which essays were written. A more rigorous test of naïve Bayes was to train the algorithm on a subset of the essays and test it on the remaining essays. This was carried out using the LOOCV method described earlier. The results of this test are summarized using the confusion matrix in Table 1. The rows in the matrix show the naïve Bayes predictions and the columns show the actual week the essays were submitted. If naïve Bayes had made perfect predictions, all essays would fall on the diagonal of the matrix. Essays off the diagonals show misclassifications.

Correct predictions from the naïve Bayes analyses are highlighted in yellow, on the diagonal, in Table 1. Overall, naïve Bayes correctly predicted 21/45 = 47% of the essays. There were, however, differences between lessons. Specifically, there was good consistency in the essays for Art 1 (Week 1, 6/9 = 67% predicted correctly), Art 3 (Week , 6/9 = 67% predicted correctly), and Narrative 2 (Week 5, 8/9 = 89% predicted correctly). In contrast, 1/9 = 11% and 0% were correctly predicted for Art 2 (Week 2) and Narrative 1 (Week 4), respectively. Considering the upper green box in Table 1, naïve Bayes correctly predicted 23/27 = 85% of the art lessons. Considering the lower green box, 10/18 = 56% of the narrative lessons were correctly predicted.

A number of trends can be observed in these results. First, the false-positive predictions for

[4] https://cran.r-project.org/web/packages/naivebayes/naivebayes.pdf

Week 1/Art 1 (i.e., row 1, columns 2-5, shaded in blue), suggest that three students (S3, S4, S9) carried forward (repeated) significant content from Art 1 (Week 1) into subsequent essays. A similar pattern appears for S7, whose essays were nearly all classified as Week 3, suggesting that there was very little change in what this student was reporting across the homework essays. Basically, the algorithm could not detect significant shifts in the content of that student's essays.

Table 1. Confusion Matrix for Naïve Bayes Predictions for the Week Students Composed Art and Narrative Essays. Students are shown as S#, e.g., S1.

		ACTUAL WEEK of LESSON				
		Week 1: Art 1	Week 2: Art 2	Week 3: Art 3	Week 4: Narrative 1	Week 5: Narrative 2
NAÏVE BAYES PREDICTION of WEEK of LESSON	Week 1: Art 1	S1, S3, S4, S5, S6, S9	S2, S3, S5	S2, S3	S4, S8, S9	S9
	Week 2: Art 2		S8		S2	
	Week 3: Art 3	S2, S7, S8	S1, S7	S1, S4, S5, S6, S7, S9	S5, S6, S7	
	Week 4: Narrative 1			S8		
	Week 5: Narrative 2		S4, S6, S9		S1, S3	S1, S2, S3, S4, S5, S6, S7, S8

Another observation is that there was only one correct prediction for Art 2 and no correct predictions for Narrative 1. These poor results prompt consideration of possible explanations. It could be that the instructors failed to deliver a coherent lesson during those weeks or that students were distracted by other activities, like job-searching or big tests and assignments in other classes. In the cases of S3 and S7, perhaps it took longer for the material to influence them, or they simply needed more time to engage with the content. These possibilities could be addressed in future iterations of the course by gathering more direct feedback from the students on the effectiveness of the lessons.

The second set of results for naïve Bayes was derived from estimates of the predictors that it used to make the classifications. The top 25 word stems out of 340, ranked by probability, used by naïve Bayes to classify essays by week are shown in Table 2 (column colors highlight groupings by week). There is little overlap in the strongest predictors used to classify essays for Weeks 1-5. The presence of distinct predictors to discriminate between the weeks is consistent with the finding above that naïve Bayes could classify new essays with some accuracy.

Table 2. Naïve Bayes Word Stems Ranked by Probability (pr) that Discriminate Week of Course

Week 1	pr	Week 2	pr	Week 3	pr	Week 4	pr	Week 5	pr
die	0.40	yes	0.38	construct	0.35	pose	0.36	narrat	0.39
treat	0.38	simpl	0.36	now	0.35	activ	0.35	done	0.36
profess	0.36	choos	0.33	plant	0.33	artist	0.33	communic	0.33
other	0.35	still	0.33	topic	0.33	begin	0.33	account	0.33
air	0.33	regul	0.33	larg	0.33	lack	0.33	studi	0.33
hard	0.33	water	0.32	hous	0.33	outsid	0.33	around	0.33
issu	0.33	best	0.32	local	0.33	requir	0.32	made	0.33
major	0.33	enough	0.32	decid	0.31	extrem	0.31	past	0.31
water	0.32	year	0.31	goal	0.31	togeth	0.31	share	0.31
reason	0.32	program	0.31	cloth	0.31	carbon	0.31	thus	0.31
specif	0.32	although	0.30	ident	0.31	site	0.31	potenti	0.31
complex	0.31	show	0.30	discuss	0.30	give	0.30	educ	0.31
line	0.31	answer	0.30	practic	0.30	provid	0.30	bring	0.31
put	0.31	profit	0.29	art	0.30	mind	0.29	creativ	0.31
surround	0.31	sourc	0.29	design	0.30	care	0.29	along	0.30
drink	0.31	destroy	0.29	give	0.30	form	0.29	find	0.30
risk	0.31	negat	0.29	new	0.30	strong	0.29	realli	0.29
part	0.30	read	0.29	materi	0.29	realli	0.29	week	0.29
well	0.30	want	0.29	includ	0.29	concern	0.29	interest	0.29
engineer'	0.30	produc	0.29	look	0.29	rule	0.29	word	0.29
regard	0.30	stop	0.29	littl	0.28	film	0.29	instead	0.29
avoid	0.29	caus	0.29	view	0.28	forget	0.29	stori	0.29
instead	0.29	just	0.29	implement	0.28	signific	0.29	great	0.29
keep	0.29	lot	0.29	sure	0.28	must	0.29	anyth	0.29
mean	0.29	wide	0.29	fact	0.27	employ	0.29	ideal	0.29

Meaning Extraction Helper (MEH) Results

MEH was used to identify the most frequent terms used in students' essays across the five homework assignments. The expectation was that, as in the case of the naïve Bayes word stems, there would be distinct differences in the word lemmas across Weeks 1-5. The frequency (fr) ranked lemmas are shown in Table 3. In contrast to the highest ranked word stems in the naïve Bayes analysis, MEH showed significant overlap in terms across the weeks. *Environment*, *environmental*, *community*, *people*, *relationship*, and *engineering*, are terms common across weeks. There are also differences. Week 1 includes reference to humans, resources, problems, issues, knowledge, and understanding, i.e., terms suggesting a more general exposition of the relationships between engineers, the environment, and communities. In contrast, Weeks 4 and 5 pick up on topics of narratives, stories, and communication. What is striking in the MEH analyses is that the highest frequency terms are shared across the five essay assignments. This may help to account for the difficulty naïve Bayes had with accurately classifying new essays, as described earlier, but it also suggests that students were maintaining a consistent theme across the essays, as intended by the essay assignment.

Table 3. Meaning Extraction Helper (MEH) Word Lemmas Ranked by Frequency (fr) for Each Week of Course

Week 1	fr	Week 2	fr	Week 3	fr	Week 4	fr	Week 5	fr
engineer	87	engineer	67	engineer	68	engineer	89	engineer	64
community	69	environment	56	community	60	community	49	narrative	47
environment	67	community	36	environment	33	environment	39	environment	47
environmental	36	environmental	22	people	22	people	21	community	36
people	27	human	20	design	21	work	19	people	23
protect	16	work	19	environmental	20	environmental	18	create	17
relationship	14	people	18	work	19	group	18	relationship	14
engineering	14	relationship	13	technology	18	relationship	17	environmental	13
resource	13	benefit	12	engineering	17	engineering	13	engineering	13
human	12	engineering	12	relationship	17	product	13	communication	12
design	12	change	11	group	13	project	12	project	11
better	12	live	10	project	12	live	11	human	11
role	11	right	10	class	10	provide	11	group	11
society	11	nature	9	protect	9	company	11	learn	11
live	10	time	9	natural	9	narrative	10	nature	10
risk	10	class	9	knowledge	8	story	10	focus	10
life	10	role	9	failure	8	time	9	story	10
natural	10	society	8	large	8	public	9	life	9
project	9	responsibility	8	time	8	understand	9	important	7
problem	9	large	8	location	8	design	9	work	7
water	8	reduce	8	create	7	communication	9	see	7
change	8	decision	8	situation	7	role	8	inspire	7
understanding	7	serve	7	resource	7	experience	8	video	7
important	7	product	7	give	7	human	8	personal	6
issue	7	see	7	don	7	case	8	change	6
knowledge	7	company	7	local	7	extreme	7	better	6

Discussion

The research design in the present project required students to respond to the identical writing prompt across five weeks of lectures, activities and discussions. In holding the task constant we hoped to more reliably examine differences in students' thinking across this time period. The present findings confirmed the utility of naïve Bayes and the Meaning Extraction Helper in identifying differences in the content of students' essays. A significant next step in this project will be to link the naïve Bayes and MEH predictors back into students' essays. This will allow additional confirmation of the reliability and validity of the present methods for identifying changes in students' thinking. It will also allow more incisive assessment of how and what students are thinking at various points during instruction.

The development and application of machine-assisted assessments could be especially helpful in classes with high enrollments where instructors have limited time to devote to assessing qualitative assignments, like essays, and providing feedback to students. These machine-assisted tools may also be helpful to instructors with small classes to the extent that they can provide insights regarding learning and instruction that are not readily apparent. In the naïve Bayes analyses presented in Table 1, examples of those types of insights might involve identifying students who are not advancing through the course content, as indicated by conceptually repetitive thinking. Another example, also suggested by Table 1, is the possibility that some lectures are ineffective in advancing learning in students.

The present study represents early attempts to use machine methods to unpack central concepts and propositions in student communications. The present study targeted a small sample of essays written in an open-ended fashion and classified simply by the week in which the essay composed, under the expectation that as the class topics changed from week to week, so would the predictors within the student essays. The results modestly supported the prediction. A more compelling test of the present methods would involve substantially larger corpora, involving pre-course and post-course essays, for example, in classes with large enrollments. These assessments could be used to examine changes in thinking potentially attributable to the course.

An area of great interest in current scholarly research involves engineering identity. Engineering educators are interested in how engineering students view themselves early on in their training [7], as well as what it means more generally to think of oneself as an engineer [23] [24]. A better understanding of how and when engineering majors identify as engineers is important for academic retention, engineering graduation rates, and professional identity. Large-scale machine-assisted assessments involving extensions of the naïve Bayes methods presented here could be implemented longitudinally, for instance, from first through senior years, and could be informative in terms of how and when students embrace an identity of "engineer."

Limitations

A strong limitation in the present study is the small sample size. It was, however, encouraging to find that the methods tested here appeared to function adequately. In the future, it is important to test and extend the present methods with larger samples as well as with different materials and a variety of classroom applications.

The present analyses used preexisting classifications (i.e., week the essay was composed) in order to train and test the naïve Bayes algorithm. This approach could be readily applied to other data, like analyzing pre-course and post-course essays, or longitudinal data by year. However, in other tests and applications, human raters would be required in order to classify training and test data, prior to the establishment of a reliable assessment database within naïve Bayes. This type of human classification would be required, for example, if texts were being classified for specific content. For instance, an instructor might be interested in whether a student's essay addressed one of several ethical issues, or one of several issues involving stakeholders. For these analyses, there would be a higher demand initially on human investment in developing a reliable database that naïve Bayes could subsequently apply to new essays independent of human input. These types of analyses await further research.

Conclusions

Machine-assisted assessment applications have not been widely implemented in engineering classrooms. The tests presented here provide positive and encouraging results that motivate further development and testing of machine capabilities. The unique perspective that the present analyses provide involves thinking about student essays and other communications, like blogs, discussion boards, design narratives, and pre- and post-assessments, in terms of the essential cognitive constructs (expressed as words) that constitute the building blocks of essays. The naïve Bayes analyses demonstrated an ability to classify essays at that level and, indeed, to classify new essays based on knowledge of prior essays.

The next goal in this work will be to recover the propositions (sentences) in students' essays that are associated with the strongest classification predictors. Simply, we want to map the predictors back into the original essays and recover the sentences (ideas) that figure most prominently in students' thinking. Recovering these central ideas will bring us closer to the ultimate goal of this project, which is to develop and assess prospective (student) reflective practitioners [25], particularly as they incorporate the ABET goals of social, cultural, environmental, and global awareness.

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References

[1] C. Baillie, "Engineers within a local and global society." *Synthesis Lectures on Engineering, Technology and* Society, vol. 1.1, 2006, pp. 1-76.
[2] C. Baillie and G. Catalano, "Engineering and society: Working towards social justice, Part III: Windows on society." *Synthesis Lectures on Engineers, Technology and Society*," vol. 4.1, 2009, pp. 1-124.
[3] G. Catalano and C. Baillie, "Engineering and society: Working towards social justice, Part II: Decisions in the 21st century," *Synthesis Lectures on Engineers, Technology and Society*, vol. 4.1, 2009, pp. 1-117.
[4] L. Lynn and H. Salzman, "Engineers, firms and nations: Ethical dilemmas in the new global environment." *Engineering Ethics for a Globalized World*, 2015, pp. 15-33.
[5] A. F. McKenna, J. Froyd, C. Judson King, T. Litzinger, and E. Seymour, "The complexities of transforming engineering higher education," *Report on Forum on Characterizing the Impact and Diffusion of Transformative Engineering Education Innovations*, National Academy of Engineering, 2011. Available from https://www.nae.edu/Projects/CASEE/CASEEProjects/26183/26293.aspx
[6] J. A. Leydens, " Sociotechnical communication in engineering: An exploration and unveiling of common myths," *Engineering Studies*, vol. 4, no. 1, 2012, pp. 1-9.
[7] H. Loshbaugh and B. Claar, "Geeks are chic: Cultural identity and engineering students' pathways to the profession," In *Proceedings, ASEE Annual Conference & Exposition,* Honolulu, HI, 2007.

[8] C. E. Harris Jr. et al., "Engineering ethics: what? why? how? and when?." *Journal of Engineering Education*, vol. 85, no. 2, 1996, pp. 93-96.
[9] C. E. Harris Jr. et al., *Engineering Ethics: Concepts and Cases*, Cengage Learning, 2013.
[10] J. S. Weedon and T. K. Fountain, "Making design thinking genre knowledge: Embodiment, typification, and engineering design," In *2019 IEEE International Professional Communication Conference,* Aachen, Germany, 2019.
[11] A. Khalid, C. Chin, M. Atiqullah, J. Sweigart, B. Stutzmann, and W. Zhou, "Building a better engineer: The importance of humanities in engineering curriculum," In *Proceedings, ASEE Annual Conference & Exposition,* Atlanta, GA, 2013.
[12] R. C. Campbell, D. D. Reible, R. Taraban, and J-H Kim, "Fostering reflective engineers: Outcomes of an arts-and humanities-infused graduate course," In *2018 World Engineering Education Forum-Global Engineering Deans Council*, pp. 1-6, IEEE, 2018.
[13] J. W. Pennebaker and L. A. King, "Linguistic styles: Language use as an individual difference," *Journal of Personality and Social Psychology*, vol. 77, no. 6, 1999, pp. 1296-1312.
[14] J. W. Pennebaker, R. L. Boyd, K. Jordan, and K. Blackburn, *The development and psychometric properties of LIWC 2015*, Austin, TX: University of Texas at Austin, 2015.
[15] S. P. Lord, E. Sheng, Z. E. Imel, J. Baer, and D. C. Atkins, "More than reflections: Empathy in motivational interviewing includes language style synchrony between therapist and client," *Behavior therapy*, vol. 46, no. 3, 2015, pp. 296-303.
[16] J. W. Pennebaker, "Theories, therapies, and taxpayers: On the complexities of the expressive writing paradigm," *Clinical Psychology: Science and Practice*, vol. 11, no. 2, 2004, pp. 138-142.
[17] D. W. Carroll, "Patterns of student writing in a critical thinking course: A quantitative analysis," *Assessing Writing*, vol. 12, 2007, pp. 213–227.
[18] J. W. Pennebaker, C. K. Chung, J. Frazee, G. M. Lavergne, and D. I. Beaver, "When small words foretell academic success: The case of college admissions essays," *PLoS ONE*, vol. 9, no. 12, 2014, pp. e115844.
[19] R. L. Robinson, R. Navea, and W. Ickes, "Predicting final course performance from students' written self-introductions: A LIWC analysis," *Journal of Language and Social Psychology*, vol. 32, no. 4, 2013, pp. 469 – 479.
[20] K. Robertson and A. Doig, "An empirical investigation of variations in real-estate marketing language over a market cycle," *Housing, Theory and Society*, vol. 27, no. 2, 2010, pp. 178-189.
[21] R. L. Boyd, MEH: Meaning Extraction Helper (Version 2.1.06) [Software], 2018. Available from https://meh.ryanb.cc
[22] C. K. Chung and J. W. Pennebaker, "Revealing dimensions of thinking in open-ended self-descriptions: An automated meaning extraction method for natural language," *Journal of Research in Personality*, vol. 42, no. 1, 2008, pp. 96-132.
[23] J. R. Morelock, "A systematic literature review of engineering identity: definitions, factors, and interventions affecting development, and means of measurement, *European Journal of Engineering Education*, vol. 42, no. 6, 2017, pp. 1240-1262.
[24] A. Godwin, "The development of a measure of engineering identity," In *Proceedings, ASEE Annual Conference & Exposition,* New Orleans, LA, 2016.
[25] D. A. Schön, *The reflective practitioner: How professionals think in action*. Routledge, 2017.