Work in Progress: Quantifying Learning by Reflecting on Doing in an Engineering Design, Build and Test Course

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Zahed Siddique is a Professor of Mechanical Engineering at the School of Aerospace and Mechanical Engineering of University of Oklahoma. His research interest include product family design, advanced material and engineering education. He is interested in motivation of engineering students, peer-to-peer learning, flat learning environments, technology assisted engineering education and experiential learning. He is the coordinator of the industry sponsored capstone from at his school and is the advisor of OU's FSAE team.

Dr. Janet Katherine Allen, University of Oklahoma

Janet Allen came to the University of Oklahoma in August 2009 where she and Professor Farrokh Mistree are establishing the Systems Realization Laboratory at the University of Oklahoma with a focus on engineering design. She holds the John and Mary Moore chair of Engineering and is a Professor of Industrial and Systems Engineering. Before coming to OU, she retired from the Woodruff School of Mechanical Engineering at Georgia Tech where she is Professor Emerita. The focus of Dr. Allen's research is engineering design and especially the management of uncertainty when making design decisions. Her group was among the first to suggest the use of modeling uncertainty in design, particularly in the early stages of design and to recognize the importance of statistical simulation and computer-based experimentation in design and was also among the first to demonstrate the importance of using the design of experiments in exploring regions of design space in order to create surrogate models. This is a necessary step in moving away from the costly and time-consuming method of testing designs by building prototypes and replacing physical prototypes with computer-based experiments. Using surrogate models lead to the investigation of various aspects of robust design of many different systems, especially multilevel and multiscale systems. A special focus has been on supporting collaborative decision making and design – several hierarchical procedures and game theory have been used to model collaborative design. Dr. Allen and her students study/have studied energy systems, mechanical systems, materials, and design methods and have published over 200 papers in journals, conference proceedings and edited books. She is a Fellow of ASME, a Senior Member of AIAA and an Honorary Member of the Mechanical Engineering Honor Society Pi Tau Sigma.

Prof. Farrokh Mistree, University of Oklahoma

Farrokh's passion is to have fun in providing an opportunity for highly motivated and talented people to learn how to define and achieve their dreams.

Farrokh Mistree holds the L. A. Comp Chair in the School of Aerospace and Mechanical Engineering at the University of Oklahoma in Norman, Oklahoma. Farrokh is a Fellow of ASME, an Associate Fellow of AIAA and a Life Member of The Honor Society of Phi Kappa Phi. He was named the ASME Ruth and Joel Spira Outstanding Engineering Design Educator in 2011. In September 2012 he was recognized as a Distinguished Alumnus of the Indian Institute of Technology, Kharagpur, India. In December 2012, he received the Life Time Achievement Award from the International Society for Agile Manufacturing, Lafayette, Louisiana.

Farrokh co-directs the Systems Realization Laboratory @ OU with his wife Professor Janet K. Allen in Industrial and Systems Engineering. The Allen-Mistree research focus is on collaboratively defining the emerging frontier for the "intelligent" decision-based realization of complex (cyber-physical-social) systems when the computational models are incomplete and inaccurate. Their quest for answers to the key challenges are anchored in five research thrusts, namely,

Contextual Assessment of Student Learning through Reflection on Doing Exploiting the Food-Energy-Water Nexus for Rural Development Integrated Realization of Engineered Materials, Products, and Associated Manufacturing Processes Knowledge-Based Dynamic Management of Multi-stage Complex Processes Knowledge-Based Management of Computational Complexity and Risk Knowledge-Based Platform for Decision Support in the Design of Engineered Systems

His current education focus is on creating and implementing, in partnership with industry, a curriculum for educating strategic engineers—those who have developed the competencies to create value through the realization of complex engineered systems.

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ABSTRACT

How can instructors leverage assessment instruments in design, build, and test courses to simultaneously improve student outcomes and assess student learning well enough to improve courses for future students?

A learning statement is a structured [Experience|Learning|Value] text-based construct for students in *AME4163 Principles of Engineering Design* to record what they learned by reflecting on authentic immersive experiences throughout the semester. The immersive experiences include lectures, assignments, reviews, building, testing and a post-analysis for design of an electro-mechanical system to address a given customer need. Over the past three years. in the School of Aerospace and Mechanical Engineering at the University of Oklahoma, we have collected almost 30,000 learning statements from almost 400 students that we propose to use to improve our understanding of what students have learned by reflecting on doing and thence how we might improve the delivery of the course.

In this paper, we briefly introduce the framework of a computer program used to process a large number of learning statements by way of providing context. We focus on comparing what students learned with what instructors expected the students to learn thus providing evidence-based guidance to instructors on how to improve the delivery of *AME4163* thus providing an initial answer to the question posed above.

1. Frame of Reference

Industry is facing an ever-changing environment. Many companies want their engineer employees to have the ability to adapt to the changing environment [1]. From the education perspective, universities or colleges are also providing programs and courses for engineering students, especially senior undergraduate students to help them develop their competencies for future careers as junior engineers when they graduate. At the University of Oklahoma(OU), AME4163: Principles of Engineering Design, a course for preparing senior undergraduate students for their future career in engineering through experiential learning [2]. Our goal in AME4163: Principles of Engineering Design (POED) is to offer Junior Engineers the opportunity to learn by reflecting on doing in an immersive authentic environment. We hypothesize that by having engineering students reflect on an experience related to a principle of engineering design and articulate a lesson learned that they will develop the ability to continue identify new principles and thence grow professionally [3]. The learning statements are the linguistic embodiment of students' engineering competencies through reflection on doing. As shown in Table 1, a learning statement is represented using a text-based [Experience|Learning|Value] construct. By this construct, students record what they learned by reflecting on authentic immersive experiences throughout the semester. The learning statements anchored in the lectures are aimed at getting students to identify a "lesson" that will be of value in completing an assignment. The learning statements anchored in assignments are aimed at helping a student transition from university to a Junior Engineer in industry.

Table 1. The Structure of the Learning Statements

Experience x	**Learning y**	**Value / Utility z**
Through **x** (From **x**, By doing **x**, …)	I learned **y**	
I did not consider **x** initially	I realized **y**	Value / utility **z**
I thought (expected) **x** before / initially	I found out **y**	in future of
	I discovered **y**	learning **y**
	I became conscious of **y**	

There are typically over 150 students attending AME4163 in each fall semester. At the end of the semester, we typically collect around 12,000 learning statements from the students about the lectures they attended and the assignments they completed. The value of these learning statements is anchored in that instructors and teaching assistants can analyze the learning statements and understand what students have individually and collectively learned and whether the outcome is in keeping with what the instructors planned. One option to do this is to have instructors and teaching assistants manually read the learning statements and assess student learning. The key disadvantage of this option is that manually dealing with a huge amount of text-based data (12,000 learning statements per semester) is labor-intensive and time-consuming. We did this for the first two years and found that maintaining consistency in the assessment was virtually impossible. Hence, our effort to develop a computational framework to aid the instructors in the assessment of the learning statements. In this paper we propose a computational text mining framework to quantify learning embodied in learning statements written by engineering students. In this paper we address the following question:

What are the functionalities of a text mining framework that can be used to allow instructors to analyze and gain insights from triplet-structured learning statements in engineering design courses?

The rest of this paper is organized as follows. In Section 2, we critically review the related work. In Section 3, we present the framework, functionalities and user interfaces of the text mining program. In Section 4, we verify the results generated by the proposed text mining program. Finally, we conclude this paper with contributions and future work in Sections 5.

2 Critical Review of Related Work

To analyze the learning statements and discover the hidden patterns, we identify four key functionalities that are needed in a text mining program, namely, data cleaning, data management, text analysis, and text visualization. In this section we present a review of the literature with respect to these four aspects, the results is summarized in Table 2. We firstly discuss the existing literatures, then compare our framework to the existing literature and identify our contributions in this paper.

Table 2. Key Papers

	Data Cleaning	**Data Management**	**Text Analysis**	**Visualization**
Mooney and coauthors [4]	√			
Xu and coauthors [5]	√			
Agichtein and coauthors [6]	√		√	
Castellanos and coauthors [7]	√			
Haddi and coauthors [8]	√			
Tang and coauthors [9]	√			
Nimmagadda and coauthors [10]		√		
Turk [11]		√		
Yafooz and coauthors [12]		√	√	
Neto and coauthors [13]			√	
Trstenjak and coauthors [14]			√	
Mahgoub and coauthors [15]	√		√	
Larsen and coauthors [16]			√	
Kucher and coauthors [17]				√
Chi and coauthors [18]				√
Kulahcioglu and coauthors [19]				√
Malheiros and coauthors [20]			√	√
This paper	√	√	√	√

Data cleaning is a very important step in a text mining program. Our goal in data cleaning is to preprocess the textual content of a document so that interesting contents are extracted or transformed to a required format. For example, Mooney and coauthors [4] discuss information extraction methods and implement systems that extract concrete text corpora of biomedical abstracts, job announcements, and product descriptions from a set of unstructured documents. Xu and coauthors [5] propose a machine-learning-based method for identifying whether a sentence in an electronic document is bad and remove bad sentences from the document. Agichtein and coauthors [6] propose an automatic segmentation method for segmenting unstructured text strings into structured records so as to facilitate importing the information contained in legacy sources and text collections into a data warehouse for subsequent querying, analysis, mining and integration. Castellanos and coauthors [7] present a method for removing or replacing dirty text from a document by leveraging existing domain knowledge. Haddi and coauthors [8] propose a method for extracting online opinions from social media big data using support vector machines. Tang and coauthors [9] propose a method for cleaning noisy data from emails which includes four passes: non-text filtering, paragraph normalization, sentence normalization, and word normalization.

Data management is used in a text mining program to capture and manage key attributes of documents or to structuralize the unstructured text so that the textual data can be accumulated in a database in a reusable and retrievable way. Data management is important because it provides a structured and organized data source for statistical analysis of the textual documents. Nimmagadda and coauthors [10] use ontologies for managing the contextual knowledge of alphanumeric textual data in a digital document ecosystem. The ontology can deliver text-mining, the semantic and schematic information of textual data, and can expedite the textual-data integration process in the multidimensional warehouse modelling procedure. Turk [11] proposes a construction design document management schema which suggests that a document should be used as a larger data chunk instead of records, attributes and primitive objects, and present the document management prototype. Yafooz and coauthors [12] propose a method to automatically organize unstructured information in relational database management systems through linkages among textual data based on semantics.

Text analysis is the core of a text mining program. Text analysis is used to discover the hidden patterns in textual documents by quantification of the text using different methods. For example, Neto and coauthors [13] propose a method for document clustering and text summarization. They use the so-called "Autoclass" for clustering the documents and use the TF-ISF (term frequency – inverse sentence frequency) measure which is an adaptation of the conventional TF-IDF (term frequency – inverse document frequency) measure to do text summarization. Trstenjak and coauthors [14] propose a text classification method by integrating the k-nearest neighbors (KNN) algorithm and the TF-IDF method. The method enables classification according to various parameters and measurements. Mahgoub and coauthors [15] propose a method for automatically extracting association rules from text by integrating XML technology with information retrieval scheme (TF-IDF). Larsen and coauthors [16] describe an unsupervised, near-linear time text clustering system that offers a number of algorithm choices for feature extraction and clustering.

Visualization in a text mining program is used to display the mining results in a meaningful way so that researchers can easily understand the patterns in the text. Kucher and coauthors [17] conduct a survey of text visualization techniques and describe the visualization tasks such as region of interest, clustering/classification/categorization, comparison, overview, monitoring, navigation, and uncertainty tract, etc. Chi and coauthors [18] propose a time-varying word cloud visualization method that uses rigid body dynamics to arrange multi-temporal word-tags in a specific shape sequence under various constraints. This method can attract people's attention by the spatial shapes and temporal motions of word clouds. Kulahcioglu and coauthors [19] present a type of word cloud that enables the selection of affect-aware font and color palette to facilitate more informed choices and generate a stronger emotional impact on users. Malheiros and coauthors [20] present a visual text mining tool to aid systematic reviews of research topics in the software research community.

As the discussion above, it is acknowledged that the functionalities of a text mining program such as data cleaning, data management, text analysis, and visualization have been well studied in the existing literature. Researchers propose methods or develop computational frameworks to address problems in specific domains (e.g., emails, social media, construction engineering documents, etc.) with emphasis of different text mining functionalities. However, to the best of our knowledge, there is a lack of a computational framework or system for mining the textual data generated in engineering courses that embodies students' learning by reflecting on doing. Voyant Tools is an open-source and web-based application for text analysis. There are many text visualization tools provided in Voyant Tools for users to gain insight into the uploaded text. However, Voyant Tools is not suitable for addressing the problem addressed in this paper due to two limitations. The first limitation is that there is a lack of data management function in Voyant Tools for managing about 30, 000 learning statements covering two sections, five assignments spanning three years. The other limitation is that Voyant Tools does not a feature to extract learning statements from the Word document submitted by students. In this paper, we propose a computational framework for mining learning statements by the integration of functionalities including data cleaning, data management, text analysis, and visualization. This framework fills the gap of text mining in the engineering education domain. In Section 3, we present the text mining framework and in Section 4 the results and interpretation of these results for use by an instructor to improve the next offering of the course.

3. The Framework of the Text Mining Program

3.1 Overview of the Framework from Users' Perspective

The text mining framework from user's perspective is illustrated in Figure 1. Data contributors are students or teaching assistants who submit or collect original learning statement documents, and then upload them to the framework for analysis. To distinguish the documents in the program, data contributors need to annotate the documents when uploading. Researchers are instructors who are interested in the knowledge hidden in the learning statements. They can review the results (numbers, graphs, word clouds, etc.) given by the text mining program and gain insight. A user can be both a data contributor and a researcher based on his/her interests. In the Section 3.2, we describe the text mining framework.

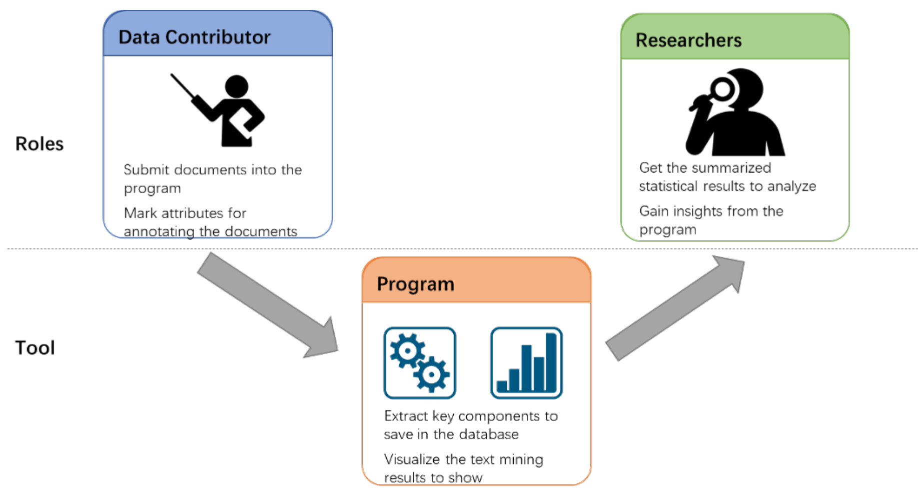

Figure 1. An Overview of the Text Mining Framework from User's Perspective

3.2 The Framework of the Text Mining Program

A schematic of the text mining framework is shown in Figure 2. The framework consists of three parts: data contributors, program, and researchers. In the framework, the actions of data contributors include 1) submitting original documents to the program, 2) setting up the matching rules for the extraction of learning statements from the original documents, and 3) annotating relevant attributes to the uploaded documents. These text documents are intended to generate the corresponding visualization results in the program. The program has four key functionalities, namely, data cleaning, data management, text analysis, and results visualization. Data cleaning is used to extract key words from the raw textual contents. Data management is to save the cleaned data into the database using structured formats. Text analysis is to analyze the stored textual data and discover the hidden patterns using various of algorithms such as word frequency, text similarity, and connection, etc. Finally, the discovered patterns will be visualized using different types of graph or chart to facilitate researchers gaining insights from the textual data. These visualization results can facilitate researchers interpreting the original text contents, answering their research questions, and creating new knowledge.

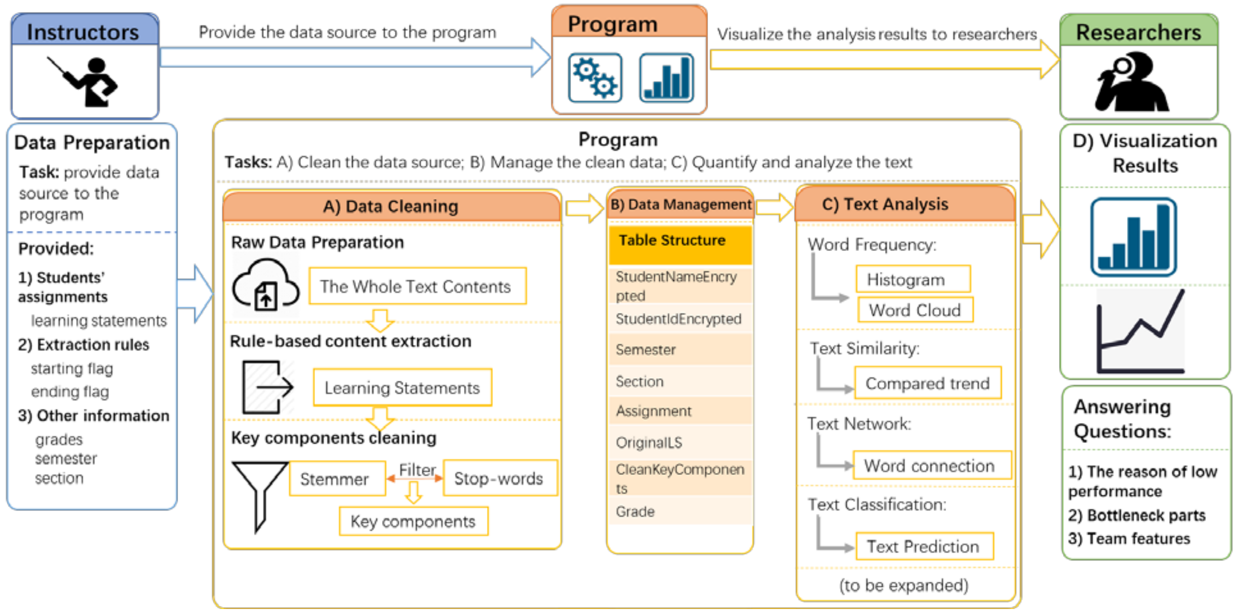

Figure 2. The Text Mining Framework for Quantification of Students' Learning Statements

The details of the four key functionalities identified in the text mining framework shown in Figure 2 are as follows.

a) Data Cleaning

The learning statements submitted by students are complete sentences which consist of different parts-of-speech including nouns, verbs, adjectives, adverbs, prepositions, and conjunctions etc. Typically, prepositions and conjunctions are the words used to keep the continuity of sentence, and they don't have practical meaning. What really means something are the nouns, verbs, adjectives, and adverbs. Therefore, there is a need to clean the sentences to retain those meaningful key components. The function of data cleaning in the program of this paper consists of three steps, as shown in Figure 3.

- **Step 1. Raw data preparation.** In this step, students prepare their learning statements using the [Experience|Learning|Value] triplet structure after they attended each lecture or finished each assignment of the course. Below is an example:

  By forming a team at the beginning of the project, I learned the importance of ensuring that all team members have the same objectives when starting a project which will be of *value to me as I will have a better understanding of important considerations when working on junior engineering teams.*

It should be noted that students are trained to use the triple structure at the beginning of the semester so that they are skilled at applying it throughout the whole semester. When the learning statements are ready, they are uploaded to the text mining program together with other background information (e.g., lecture information, problem description, solutions, etc.) archived in the same document. The uploading of documents can also be done by teaching assistants who collect the submissions and batch-upload to the program.

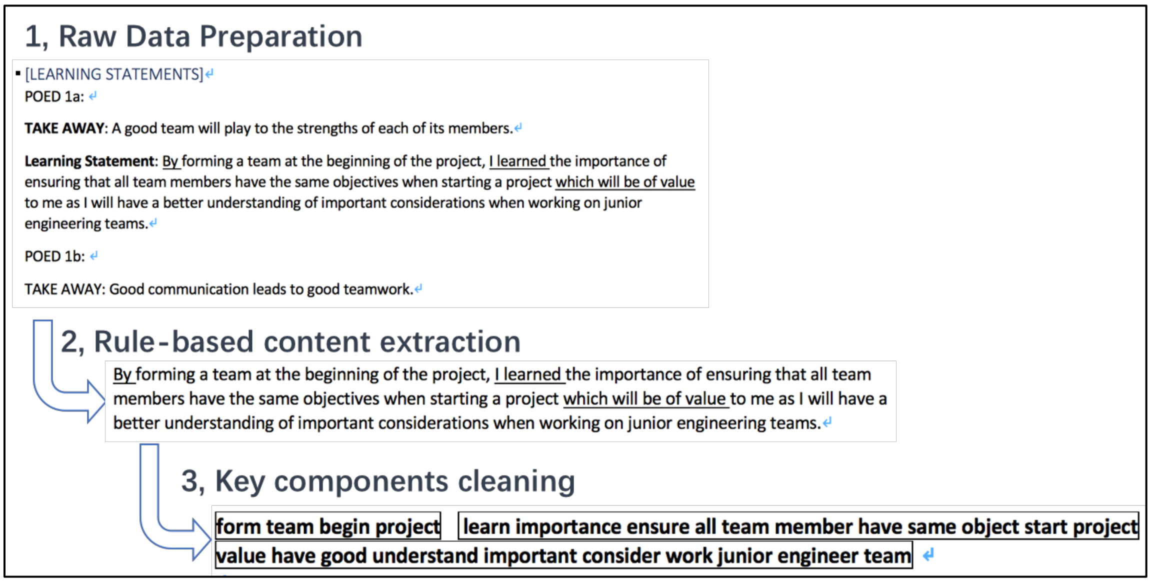

Figure 3. The Workflow of the Functionality of Data cleaning

- **Step 2. Rule-based content extraction.** As mentioned in Step 1, the documents uploaded by data contributors not only include learning statements, but also other background information. We need to extract learning statements from the documents. For example, some learning statements may be located in a document as follows:

…
Learning Statement: *By forming a team at the beginning …*
…

In order to extract the above learning statement from the whole document, we first to locate in the position where the statement begins, namely, the phrase “Learning Statement:”. This is can be done by setting up the matching rule to match “Learning Statement:”, and then extracting the sentence right after it. The extraction is terminated when it reaches a period or a linefeed.

- **Step 3. Key components cleaning.** In this step, the program will automatically filter meaningless words and characters from the textual contents using stemming and stop-words-based method. stemming is the process of reducing inflected (or sometimes derived) words to their word stem, base or root form—generally a written word form. The stem need not be identical to the morphological root of the word, it is usually sufficient that related words map to the same stem, even if this stem is not in itself a valid root. In the program of this paper, we use stemming method convert all the meaningful components to their root form. For example the word “begins” is converted to “begin”, the word “better” is converted to “good”. In computing, stop words are words which are filtered out before processing of natural language data (text). Stop words are generally the most common words in a language. In the program of this paper, we use stop-words-based method to filter meaningless words such as “a”, “the”, “by”, “of”, “and”, “but”, etc.

b) Data Management

A learning statement submitted to the text mining program can have many attributes, such as the student who wrote it, the semester when the learning statement was generated, the section of the course taught by a particular instructor, and the assignment based on which the learning statement was created, etc. These attributes, together with the learning statement itself, are very important for future analysis when large number of learning statement are accumulated. For example, researchers can compare the learning statements generated in two different sections of the same semester, to see the difference of focus between the instructors who taught the two sections. In this paper, we create a data structure, as shown in Table 3, to capture the associated attributes of learning statements and permanently store the attributes as well as the learning statements in a database. The database provides a formal source of data for analysis in the next stage of the text mining program.

Table 3. Specification of Attributes for Data Management

Attribute	Explanation
StudentNameEncrypted	Captures the encrypted student name.
StudentIdEncrypted	Captures the encrypted student ID.
Semester	Captures the semester to which the learning statement belongs, for example, Fall2018, Fall2019, etc.
Section	Captures the section to which the learning statement belongs, for example, Section 001 (Taught by Instructor A), Section 002 (Taught by Instructor B), etc.
Assignment	Captures the assignment from which the learning statement was generated, for example, Assignment 1 (Team Formation), Assignment 2 (Conceptual Design), etc.
OriginalLS	Captures the original learning statement before it is cleaned.
CleanKeyComponents	Captures the key components of the learning statement after it is cleaned.
Grade	Captures the grade given by the instructor or teaching assistant in terms of the student’s performance in the assignment.

c) Text Analysis

There may be many patterns hidden in the learning statements stored (or accumulated) in the database. One of these patterns is that the occurrence frequency of some words are relatively high in the learning statements associated with some particular assignments. For example, "team" and "project" are the high-frequency words in the learning statements associated with assignment of team formation. Another pattern is that the learning statements of those students whose grade are relatively high are typically more relevant (or similar/close) to the requirements (the engineering design principles in the AME4163 course) of the assignments. For example, in the assignment associated with conceptual design, the learning statements of the students who perform well should be more relevant to principles of selection, evaluation, etc. Other patterns include the correlation of the learning statements of the members in a team, and the correlation of the learning statements associated with the sections taught by different instructors in one course etc. In order to discover these patterns, we need to quantify the text. In the text mining program of this paper we implemented several text quantification methods, such as term frequency (TF), inverse document frequency (IDF, measures how important a term is in a document), word vector, and text similarity, as shown in Equations 1-4, respectively.

$$\textbf{Term Frequency: } TF(t, D) = N(t, D)/\|D\| \tag{1}$$

wherein, t stands for a specific term, D stands for a specific document that contains Term t, $N(t, D)$ stands for the number of times Term t occurs in Document D, and $\|D\|$ means the total number of terms contained in document D.

$$\textbf{Inverse Document Frequency: } IDF(t) = 1 + \log\left(\frac{DF(t)}{N}\right) \tag{2}$$

wherein, N means the total number of documents, $DF(t)$ means the number of documents with Term t.

$$\textbf{TF-IDF: } TI_t = TF(t, D) * IDF(t) \tag{3}$$

$$\textbf{Word Vector: } \quad Vector(D) = \left[TI_{t_1}, TI_{t_2}, \dots TI_{t_i}, \dots TI_{t_n}\right] \; i \in n \tag{4}$$

wherein, TI_t stands for the TF-IDF computing result of a term in the document, $Vector(D)$ means the vector of the document embodied by all terms' TF-IDF values.

Text Similarity:

$$TS(D_1,\ D_2) = cos < Vector(D_1),\ Vector(D_2) >= \frac{Vector^T(D_1) * Vector(D_2)}{\|Vector(D_1)\| * \|Vector(D_2)\|} \tag{5}$$

wherein, $TS(D_1,\ D_2)$ stands for similarity between two texts measured by the cosine value of the two texts.

d) Visualization of Results

The quantification results after text analysis need to be displayed in an intuitive way so that the patterns hidden in the learning statements are explicitly shown to researchers for gaining insights.

In the text mining program of this paper, we exploit graphical tools such as word cloud, histogram, and line chart, etc. to visualize the text quantification results. Word cloud is a plot that indicates the frequencies of words of a document by the sizes of words shown in the plot (the colors of the words can also be used to indicate some particular type feature of the words). The advantage of word cloud is anchored in that researchers can quickly locate the words with highest frequencies and learn about the emphasis of learning statements. Histogram is another plot to show the emphasis of learning statements in a different way. Compared to word cloud, histogram is used to show the ranking of different words by their frequencies and provide the numeric value of frequency of each word. Line chart is used to show the evolving trend of a particular feature of learning statements. For example, we can use a line chart to indicate how the similarity between students' learning statements and the principles of the course evolves as the semester moves ahead.

3.3 User Interfaces of the Program

In the text mining program, we create two user interfaces, namely, the text pre-processing interface and the text analysis interface, as shown in figures 4 and 5 respectively. The text pre-processing interface is used for users to upload original documents and attach attributes to the documents to be uploaded. In the text pre-processing interface, users click the "upload" button, select the document that they want to upload, fill in the attribute fields (i.e., Semester, Section, Assignment) to attach associated attributes to the text documents, and click the "submit" button to finish the uploading. In the text analysis interface, users fill in the condition fields (i.e., Semester, Section, Assignment, POED, Grade) to set up the scope to fetch learning statements from the database, and click the "Text Mining" button to see the plots of the text mining results.

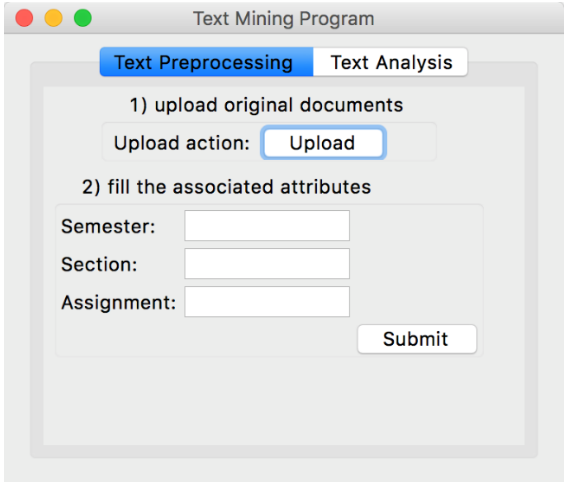

Figure 4. The Text Preprocessing Interface

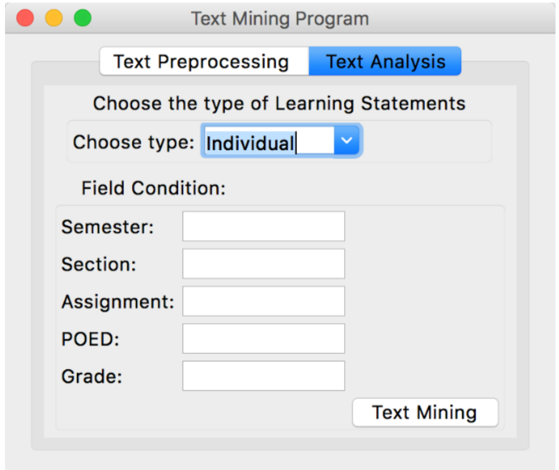

Figure 5. The Text Mining Interface

4. Mining Results of Students' Learning Statements and Discussion

In this section, we analyze the output from the text mining program and comment on it. It is seen that the text mining program can be used to quantify the learning statements (based on term frequency) and display the results in an intuitive, visual manner (e.g., word cloud and bar chart). By comparing the target POED of each assignment with mining results of learning statements, we gain insights about whether students have well internalized the POEDs and decide what needs to be fixed in Fall 2020.

4.1 The Requirements of the Course

Our goal in AME4163 is to provide an opportunity for students as junior engineers to internalize the POED and to develop competencies that they need to hit the road running as junior engineers in their capstone course and in industry after they graduate. In AME4163, students must complete a semester-long design, build and test project with a team of their colleagues. The focus of the course is not just on how well students' project devices perform, but also on students' learning. By the time they finish the project, they should be able to i) plan a design process by understanding requirements, implement that process, evaluate the outcome, and identify improvements to that process; ii) generate, evaluate, and develop design concepts by applying knowledge of science, engineering techniques, and manufacturing principles; iii) use analysis and simulation tools to understand design performance and then improve the design; iv) generate solid models and engineering drawings of the design using 3D modelling software; v) prototype the design; and vi) learn through reflecting on doing (for example, design, build, test, read, write, etc.) and experiencing (for example, working in a team, getting feedback from mentors). These abilities must be developed by internalizing the related engineering design principles covered in lectures of the course, as shown in Figure 6. The principles are associated with five key design stages, namely, 1) planning a design process, 2) preliminary design, 3) embodiment design, 4) prototyping, testing and post-mortem analysis, and 5) learning through doing, reflecting and articulating. Specific principles of each design stage are identified in Figure 6.

1. **Planning a design process**
    a. Forming a team
    b. Accepting and executing a team contract to stipulate ethical guidelines to decision making and problem resolution
    c. Understanding the problem and framing the problem statement
    d. Proposing a plan of action
2. **Preliminary design**
    a. Ideating and generating concepts
    b. Developing concepts to ensure functional feasibility, ensure realizability (technical feasibility)
    c. Evaluating the concepts (functional feasibility, technical feasibility) and identifying that system concept which is most likely to succeed
3. **Embodiment design**
    a. Refining / modifying the most likely to succeed concept through technical analysis, experimentation and thought exercises
    b. Stipulating available assets
    c. Ensuring functional feasibility, technical feasibility, realizability (buildable within budget and with available skills), and safety
4. **Prototyping, testing and post-mortem analysis**
    a. Creating a bill of materials as built, including an understanding of the limitations and capabilities of the chosen components
    b. Ensuring that the design as built meets target performance requirements
    c. Performing a critical analysis after device prototyping of causes of success and failure
5. **Learning through doing, reflecting and articulating**
    a. Critically evaluating the processes of designing, building, and testing
    b. Articulating, using learning statements, the Principles of Engineering Design that you have internalized
    c. Identifying new POED and carrying that knowledge into future projects and experiences

Figure 6. POED in AME4163

In order to help students internalize the POED, we design seven assignments for students to finish during the semester. Table 4 is a scaffolded structure to map the target POED to the specific assignments in which they appear. For example, in Assignment 1 (Table 4, Column 2), given a story and a team contract students are required to provide Problem Statement, Plan of Actions, House of Quality, Requirements List, and the Learning Statements. In this assignment, target POED include 1a, 1b, 1c, 1d, and 5b (see Figure 6 for details). These are the explicit instructor learning targets for each assignment. It should be noted that students may also reflect on connections between POED and assignments not made explicit by Table 4. By leveraging the information in Table 4, we can judge whether students' learning (reflected by text mining results) in each assignment meets the target POED.

Table 4. Structure for Scaffolding the POED and the Assignments

Assignment / Description / Target POED	1	2	3	4	5	6	7
	Given: Story, Team Contract ***Provide:*** Problem Statement, POA, HOQ, Req. List, LS	***Given:*** Prob. Statement, HOQ, Req. List. ***Provide:*** Function Structure, Morph. Chart, 6 Concepts, PMI, Failure, LS	***Given:*** Concepts, PMI, Failure ***Provide:*** Go/No-Go from 6 to 2, Bill of Materials, Select Concept, LS	***Given:*** Selected Concept ***Provide:*** Geometry analysis, CAD model, refined Bill of Materials, Buildability, Report, LS	Post-Mortem Report	Semester Learning Essay	Capstone Plan of Action
1a	✘						✘
1b	✘						✘
1c	✘						✘
1d	✘	✘	✘	✘			✘
2a		✘					
2b		✘					
2c		✘					
3a			✘				
3b			✘				
3c			✘				
4a				✘			
4b				✘			
4c				✘			
5a					✘	✘	
5b	✘	✘	✘	✘		✘	✘
5c					✘	✘	✘

4.2 Mining Junior Engineer's Learning Statements

In this section we illustrate the word clouds and the bar charts based on the analysis of data collected in three offerings of the course, namely, Fall 2017, 2018 and 2019. We comment on what can be gleaned from each and what changes the instructors plan for Fall 2020.

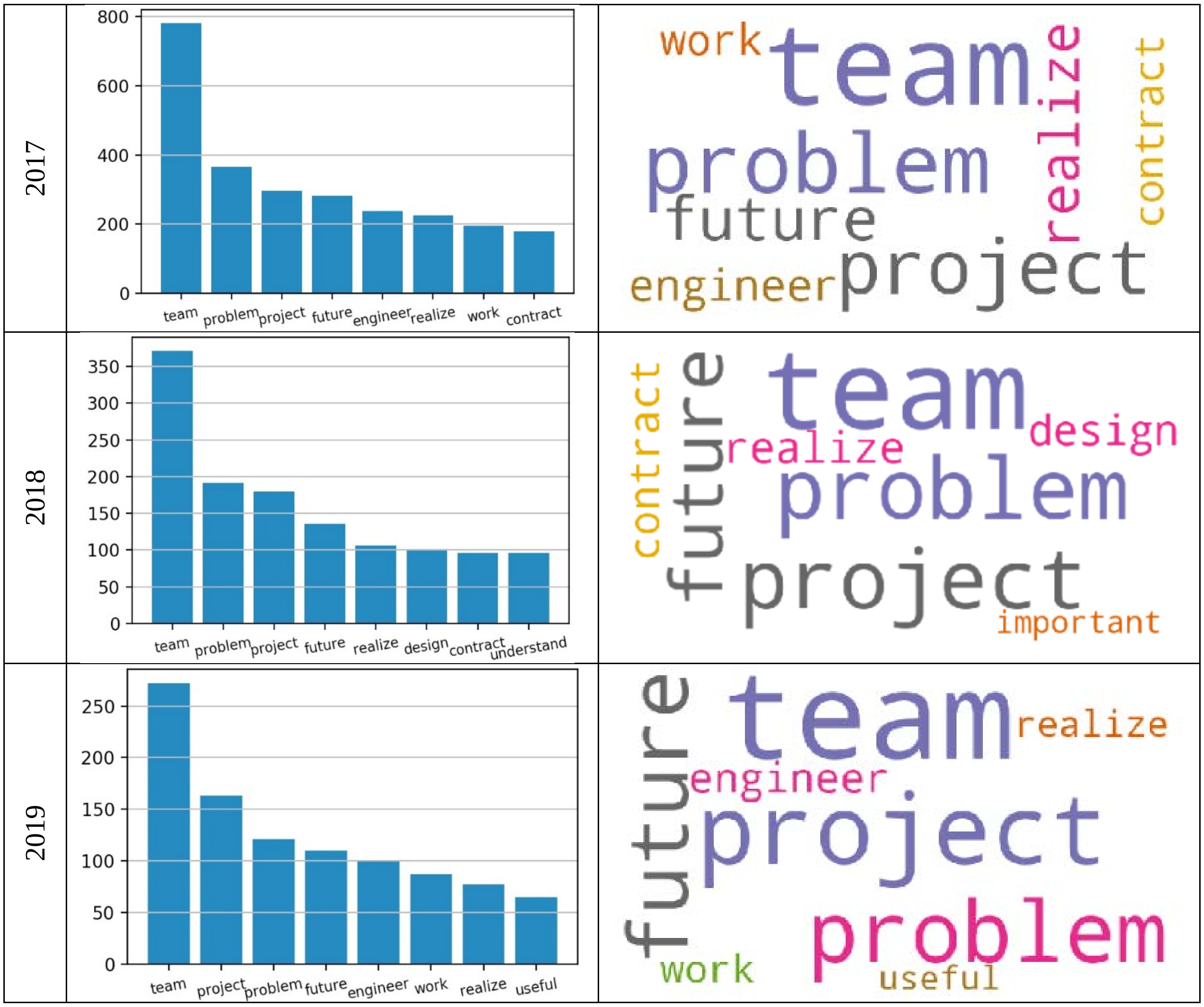

Figure 7. Mining results on Assignment 1 (For Given and Provide see Table 4)

Commentary: In Assignment 1, it is expected that keywords such “problem”, “team”, “contract”, “requirement”, “list”, etc. should appear frequently the Junior Engineer’s learning statements. From the results, shown in Figure 7, we observe that “problem”, “team” are ranked within the top 8 most frequent words in all three years, which means that most of the Junior Engineers have internalized the associated concepts and this is reflected in their learning statements. Another observation is that the word “contract” appears as top-8 in 2017 and 2018, but does not appear in the same rank 2019, which means that the concept of “contract” was not attached too much importance in 2019. Similar issue is found in terms of the words of “requirement” and “list”. These two words do not appear in the top-8 rank of all the three years. Based on these observations the instructors in 2020 will fix the associated lectures so that Junior Engineers pay more attention to the twin concepts of “contract” and “requirement list”.

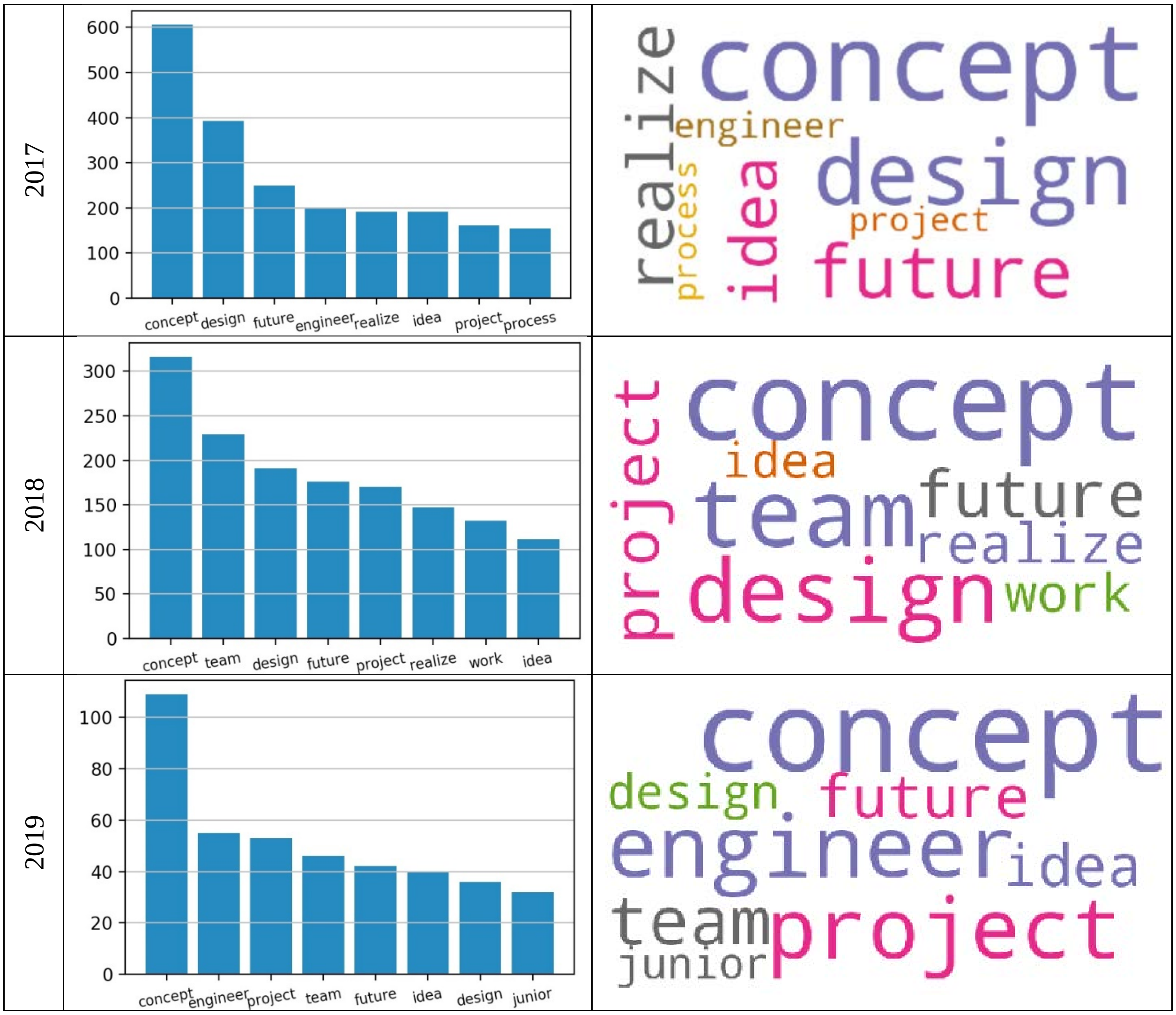

Figure 8. Mining results on Assignment 2 (For Given and Provide see Table 4)

Commentary: In the past three years we emphasized function structure and concept generation (the teams are required to generate 6 distinct concepts). We are pleased to see that the word Concept shows up in all three years. In Fall 2019 we emphasized our goal to provide an opportunity for the Junior Engineers to hit the road running. We are pleased to see that the word "Junior" shows up in the word cloud for 2019. We expect that keywords such as "concept", "generate", "function" etc. should appear frequently in Assignment 2. We observe from the word clouds in Figure 8 that "concept" ranks at the top of the most frequent words in all three years, which means that it was internalized, as expected, in Assignment 2. We do not see that the word "generate" appearing in the top-8 most frequent words list in 2017, 2018, and 2019. But its synonym – "idea" (which is the root of "ideating") appears in the word cloud and the bar chart, which means that students have internalized the process of ideating and generating concepts. The word "function" does not appear in the word clouds and bar charts of Figure 8, which means that "function" was not frequently mentioned in learning statements from 2017 to 2019. Therefore, the instructors will modify the lectures to place more importance on the POEDs associated with functional feasibility and realizability. In Fall 2020 we also plan to emphasize the importance of the relationship between the Requirements List (Assignment 1) and the Function Structure (Assignment 3).

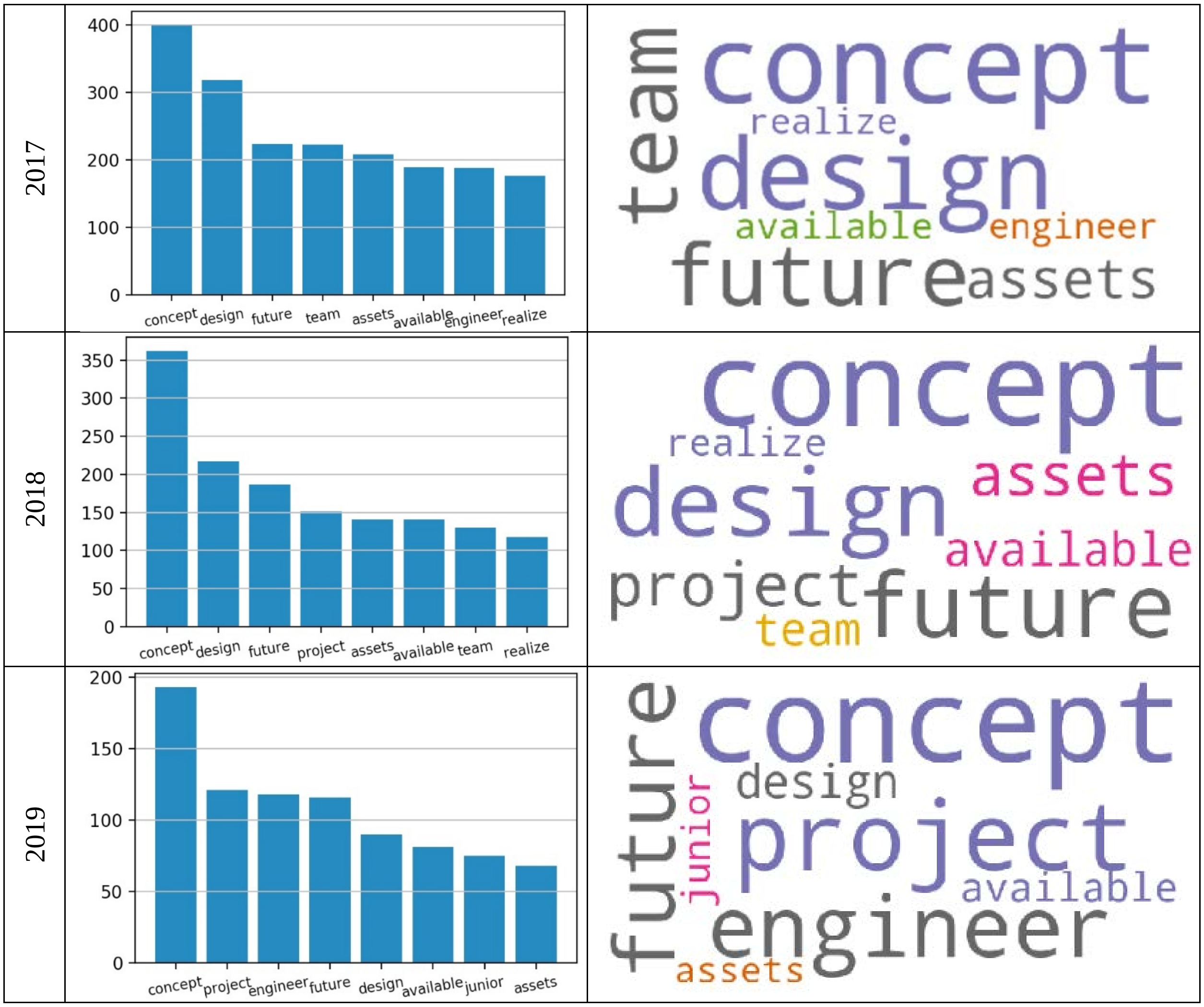

Figure 9. Mining results on Assignment 3 (For Given and Provide see Table 4)

Commentary: In Assignment 3, students are expected to mention keywords such as "concept" and "assets" in their learning statements. It is observed in Figure 9 that these words appear in the word clouds and the bar charts for all the three years, which means that students have well internalized the target POEDs in Assignment 3. Therefore, it is safe to say that the lectures designated for the target POEDs produced good results in students' learning in 2017, 2018, and 2019. In Assignment 3 students down-select, taking into account functional and technical feasibility, from 6 concepts (generated in Assignment 2) to 2. Foundational to the down-select procedure is the creation of an available assets list and buildability/realizability. We are pleased to see that the phrase "available assets" appears in all three word clouds. Realizability appears in the first two years but does not appear in the word cloud for 2019. This needs to be adjusted for in Fall 2020. We are pleased to see Junior Engineer appearing in the word cloud for 2019.

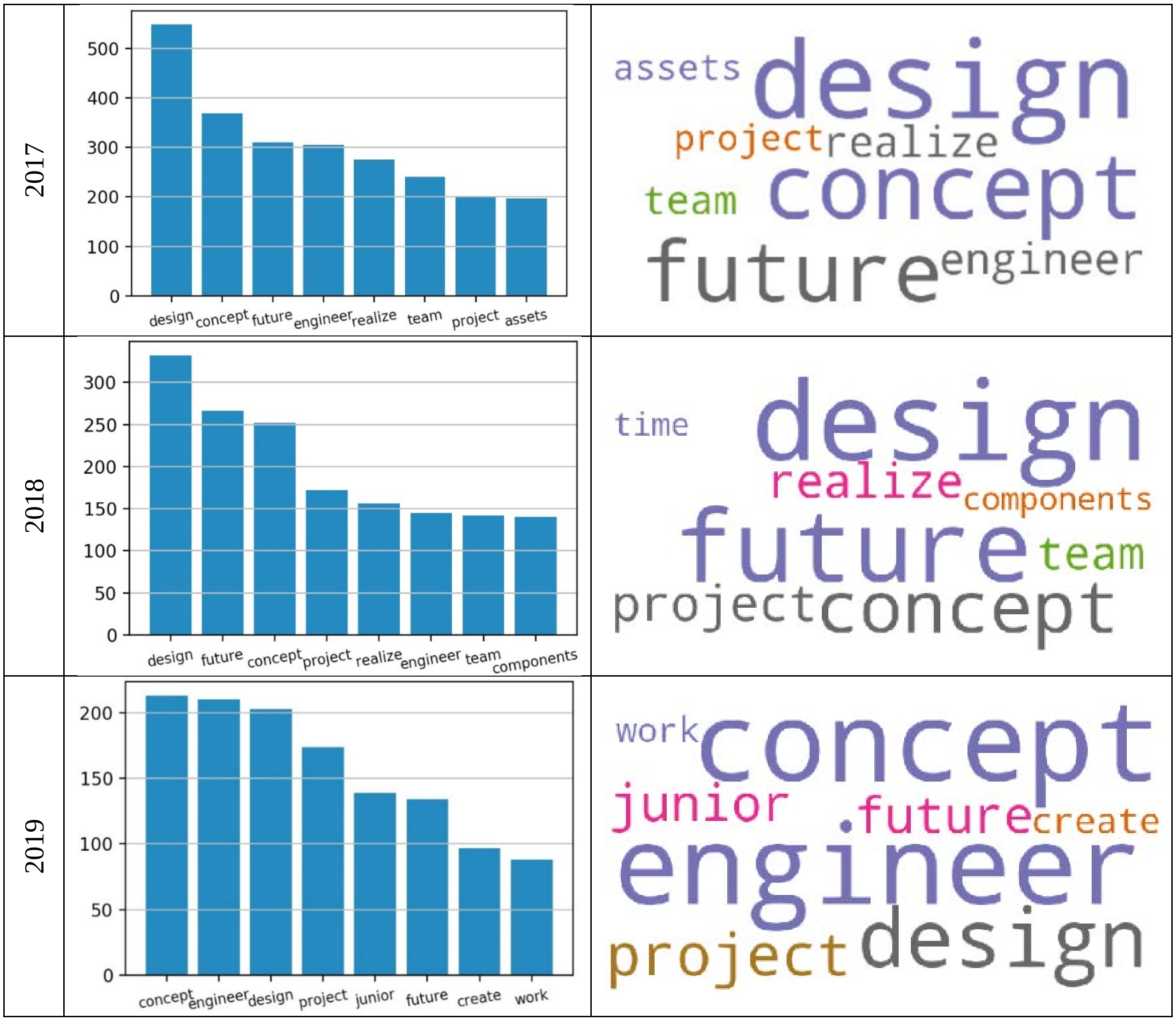

Figure 10. Mining results on Assignment 4 (For Given and Provide see Table 4)

Commentary: It is expected in Assignment 4 that keywords such as “concept” and “assets” should also frequently mentioned in the learning statements. It is observed from Figure 10 that “concept” appears in the word clouds and bar charts of all the three years, “asset” only appears in the visualization results for 2017 and disappears in both 2018 and 2019. In 2017 and 2018 the Junior Engineers were contemplating their Future. In 2019 the word Junior comes to the fore. Regrettably, the word Buildability / Realizability did not show up in any of the word clouds. We plan to fix this in Fall 2020.

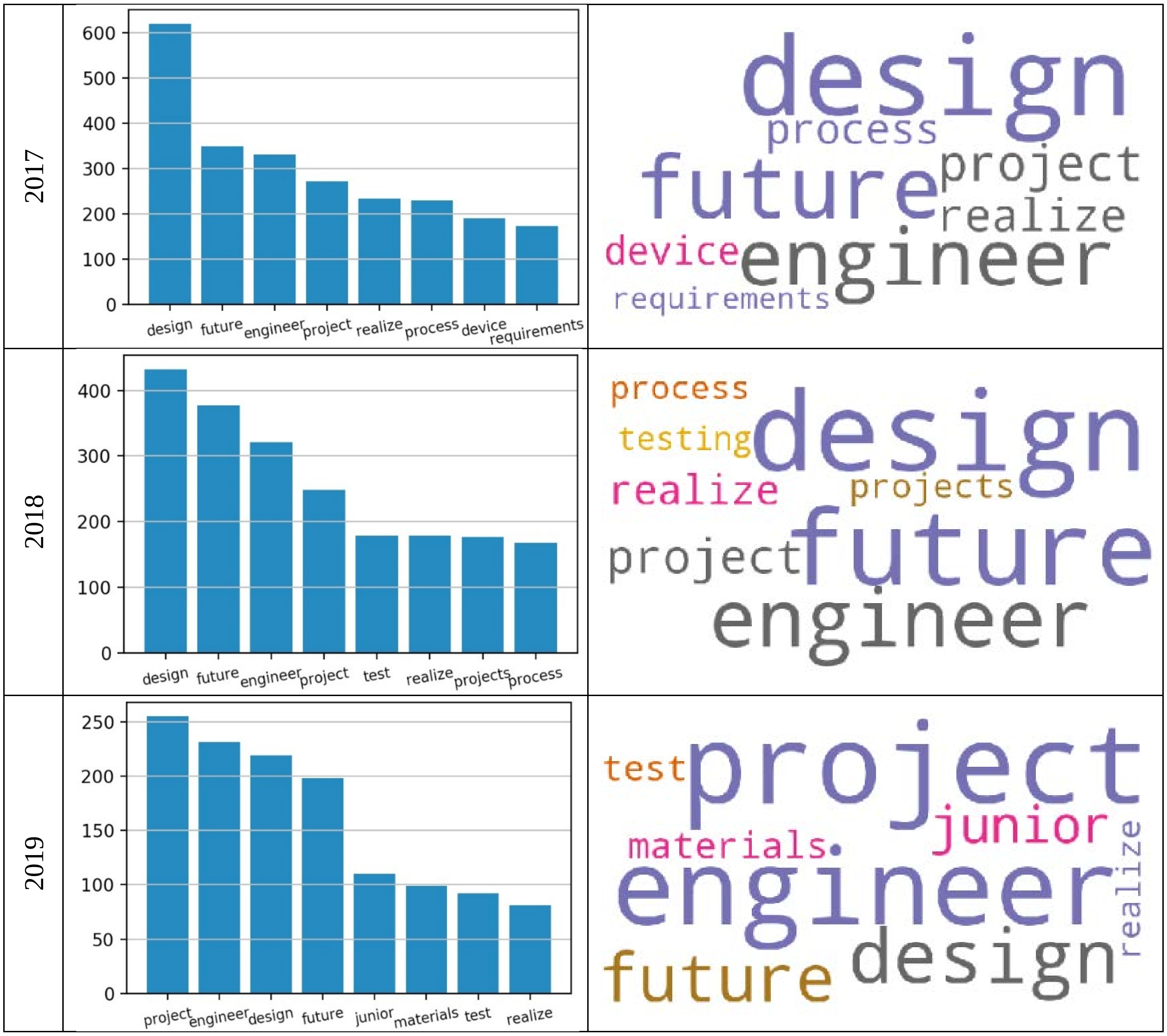

Figure 11. Mining results on Assignment 5 (For Given and Provide see Table 4)

For Assignment 5 only one POED, namely, 5c Identifying new POED and carrying that knowledge into future projects and experiences is targeted; see Figure 6. In Assignment 5, it is expected that keywords such "design", "project", "success", "failure", "engineer", and "future" should be mentioned frequently in the learning statements. In Figure 11, we observe that "design", "project", "engineer", and "future" appear in the word clouds and bar charts of 2017, 2018, and 2019, which means that students have internalized the associated target POEDs in Assignment 5. However, both "success" and "failure" are not found in the visualization results, which means that very few students (if not none) analyzed what went right, what went wrong and how to fix in their learning statements. The instructors need to rethink how to structure this assignment and perhaps include a lecture emphasizing the importance of learning how to create new POEDs.

5. CLOSURE

5.1 What is Presented in the Paper?

In this paper, we discuss the text mining framework and the implementation progress of the text mining program to answer the following question:

> *How can a text mining framework be used to allow users to gain insights from the original text source?*

With the results shown in Section 4, we summarize some conclusions for instructors and gained insights for evaluating students' learning in engineering design course. The text mining program is used to transform text into word clouds for instructors and researchers to easily analyze and draw conclusions. In the text mining program, there are four key functionalities to implement for the word-visualization transformation: data cleaning, data management, text analysis, results visualizing. In the functionality of data cleaning, the key components of learning statements are extracted for the future computing and analyzing. Data management is the functionality for users to analyze the past data flexibly. Text mining algorithms in the functionality of text analysis are used to compute the cleaned data and get the results for visualization.

Our contributions to the Design in Engineering Education Division (DEED) are that we address the problem of quantitatively assessing student learning in an engineering design, build and test course. We propose a text mining based approach to address the problem. We believe that we have touched upon DEED's twin objectives, namely, to identify problems and needs in engineering design education, and to disseminate new approaches in engineering education.

5.2 Relevance to Different Stakeholders

The framework presented I this paper is of relevance to different stakeholders. We have, however, only described that which is relevant to instructors.

1) *Relevance to instructors:* The text mining program is designed to help instructors to analyze learning statements and other text documents objectively and efficiently. Through the implementation of the text mining program, instructors can easily find out the key components in student's learning statements, and gain insights from word clouds. With more text mining algorithms and visualization methods we will be able ascertain deeper insight into what students learn and how instructors can improve the next offering of their courses.
2) *Relevance to students:* Learning statements are one way for students to learn by reflecting on doing. We envisage this framework being augmented for students to get instant feedback on their submissions so they are able to reflect and self-correct / self-learn without assistance from their instructors.
3) *Relevance to educators*: For educators, students' learning statements reflect their learning in the course to help instructors evaluate students. The proposed text mining framework helps educators easily and efficiently find out the insights in the visualization results. Educators could use these insights to improve the future engineering course for better instructing.

4) *Relevance to researchers:* The text mining framework helps researchers to quickly understand students' learning in the engineering course with the visualization results of learning statements. Researchers would develop the text mining methods for more exploring in the engineering education domain. The text mining framework could be extended by researchers to other domains.

5.3 Way Forward

In the future, the text mining program will be modified to include additional algorithms to analyze the text, for example, K-means Clustering Algorithm, Text Classification Algorithm. With these algorithms in place we should be able to answer questions such as:

- What is the difference in learning by Junior Engineers registered in two sections of this course each being orchestrated by a different instructor?
- How can we improve the experience to enhance learning of the Junior Engineers?
- How can we identify students who are likely to shine in this course early on?
- What are the characteristics of a team that performs well in the assignments and the characteristics of a team whose robot is super?
- What will be the impact of rewording the POEDs in keeping with Bloom's Taxonomy?

Clearly, what we have presented in this paper is work in progress. We look forward to collaborating with faculty who are interested in answering the question we posed in the abstract:

> *How can instructors leverage assessment instruments in design, build, and test courses to simultaneously improve student outcomes and assess student learning well enough to improve courses for future students?*

REFERENCES

[1] F. Mistree, 2013, "Strategic Design Engineering: A Contemporary Paradigm for Engineering Design Education for the 21st Century?" Journal of Mechanical Design, vol. 135, no. 9, pp. 1

[2] J. L. Autrey, J. M. Sieber, Z. Siddique, and F. Mistree,"Leveraging Self-Assessment to Encourage Learning Through Reflection on Doing," International Journal of Engineering Education, vol. 4, no. 2(B), pp. 708-722., 2018.

[3] J. Turns, W. Newstetter, J. K. Allen, and F. Mistree, "Learning Essays and the Reflective Learner: Supporting Reflection in Engineering Design Education," Proceedings of the ASEE Annual Conference, vol. 2, p. 1, 1997 Paper Number: 223001.

[4] R. J. Mooney and R. Bunescu, "Mining Knowledge from Text Using Information Extraction," ACM SIGKDD Explorations Newsletter, vol. 7, no. 1, pp. 3-10, 2005.

[5] L. Xu and H. C. Lee, "System and Method for Text Cleaning by Classifying Sentences Using Numerically Represented Features," Google Patents, 2013.

[6] E. Agichtein and V. Ganti, "Mining Reference Tables for Automatic Text Segmentation," Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2004, pp. 20-29.

[7] M. Castellanos and J. R. Stinger, "Method and System for Mining a Document Containing Dirty Text," Google Patents, 2005.

[8] E. Haddi, X. Liu, and Y. Shi, "The Role of Text Pre-Processing in Sentiment Analysis," Procedia Computer Science, vol. 17, pp. 26-32, 2013.

[9] J. Tang, H. Li, Y. Cao, and Z. Tang, "Email Data Cleaning," Proceedings of the Eleventh ACM SIGKDD International Conference on Knowledge Discovery in Data Mining, 2005, pp. 489-498.

[10] S. L. Nimmagadda, D. Zhu, and T. Reiners, "On Managing Contextual Knowledge of Digital Document Ecosystems, Characterized by Alphanumeric Textual Data," Procedia Computer Science, vol. 159, pp. 1135-1144, 2019/01/01/ 2019, doi: https://doi.org/10.1016/j.procs.2019.09.282.

[11] Z. Turk, "Construction Design Document Management Schema and Prototype," The International Journal of Construction Information Technology, vol. 2, no. 4, pp. 63-80, 1994.

[12] W. M. Yafooz, S. Z. Abidin, N. Omar, and R. A. Halim, "Model for Automatic Textual Data Clustering in Relational Databases Schema," in Proceedings of the First International Conference on Advanced Data and Information Engineering (DaEng-2013), 2014: Springer, pp. 31-40.

[13] J. L. Neto, A. D. Santos, C. A. Kaestner, N. Alexandre, and D. Santos, "Document Clustering and Text Summarization," 2000, CiteSeer[x].

[14] B. Trstenjak, S. Mikac, and D. Donko, "KNN with TF-IDF Based Framework for Text Categorization," Procedia Engineering, vol. 69, pp. 1356-1364, 2014.

[15] H. Mahgoub, D. Rösner, N. Ismail, and F. Torkey, "A Text Mining Technique Using Association Rules Extraction," International Journal of Computational Intelligence, vol. 4, no. 1, pp. 21-28, 2008.

[16] B. Larsen and C. Aone, "Fast and Effective Text Mining Using Linear-Time Document Clustering," Proceedings of the Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1999, pp. 16-22.

[17] K. Kucher and A. Kerren, "Text Visualization Techniques: Taxonomy, Visual Survey, and Community Insights," in 2015 IEEE Pacific Visualization Symposium (PacificVis), 2015: IEEE, pp. 117-121.

[18] M.-T. Chi, S.-S. Lin, S.-Y. Chen, C.-H. Lin, and T.-Y. Lee, "Morphable Word Clouds for Time-Varying Text Data Visualization," IEEE Transactions on Visualization and Computer Graphics, vol. 21, no. 12, pp. 1415-1426, 2015.

[19] T. Kulahcioglu and G. De Melo, "Paralinguistic Recommendations for Affective Word Clouds," Proceedings of the 24th International Conference on Intelligent User Interfaces, 2019, pp. 132-143.

[20] V. Malheiros, E. Hohn, R. Pinho, M. Mendonca, and J. C. Maldonado, "A Visual Text Mining Approach for Systematic Reviews," First International Symposium on Empirical Software Engineering and Measurement (ESEM 2007), 2007: IEEE, pp. 245-254.