Innovators, Learners, and Surveyors: Clustering Students in an Innovation-Based Learning Course

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***Abstract*—This full research paper aims to better understand how students create and innovate. As technology and the world around us rapidly evolve, engineers must rise to meet the needs of a future that we might not be able to even imagine yet. In order to prepare engineering students to meet future needs, it is imperative that they are given opportunities to grow in their technical abilities, but also their creativity and critical thinking. However, these skills can be difficult to teach and assess because they can manifest differently in all students. Therefore, this work aims to better understand how students approach open-ended problems, specifically in an upper level engineering course. In order to keep track of their progress and demonstrate their learning, all students uploaded self-created learning objectives and corresponding deliverables to an online platform. Clustering algorithms were then applied to the data and four clusters emerged: Innovators, Learners, Surveyors, and Surface Level. These clusters were then defined in the context of the Cynefin Framework, Bloom's Taxonomy of Learning, and Webb's Depth of Knowledge. By observing which students fell into each of the clusters, how they moved amongst the clusters, and key words associated with each cluster, we were able to better understand how students approach the process of innovation.**

***Index Terms*—clustering, innovation, experiential learning**

I. Introduction

The National Academies paints the picture of the Engineer of 2020: well-versed in science and mathematics, but also creative, innovative, and able to quickly adapt and learn [1]. Not only do these engineers fill traditional roles that prize many technical competencies, but they also fill jobs in engineering, law, medicine, business, and beyond, which require leadership, communication, and big-picture thinking. During the traditional undergraduate engineering education, students have many opportunities to grow in their technical abilities. However, less opportunities are afforded for developing non-technical competencies [2], [3].

An upper division cardiovascular engineering course gave students the opportunity to choose their own pathway to success by allowing them to work on competencies not explicitly addressed in other engineering courses. Rather than being assessed on homework, quizzes, and tests, student teams formulated and worked on innovation projects to demonstrate their learning in the course. This assessment framework, called Innovation-Based Learning (IBL), gave students the freedom to demonstrate their learning by defining their own learning objectives and deliverables. Every student approaches the course differently, and they find success in different ways. Previous work has explored the IBL assessment model and what factors lead to success, but questions still remain about identifying patterns in how students approach the course. This work aims to use unsupervised machine learning to group similar student approaches from data obtained during the course. By understanding the characteristics of these groups and how each of them develops through the course, we hope to provide better guidance to students in IBL courses and engineering more broadly.

This paper will discuss the need for students that can solve complex problems, share background about the course and dataset, explain the data mining clustering process and instructor interviews, and compare results from both methods. Then, we will share a snapshot of how each of the four clusters (Innovators, Learners, Surveyors, and Surface Level) approach the course by exploring the common traits that emerge. Finally, we will discuss takeaways for both instructors of the course and engineering instructors more broadly.

II. Background

A. The Century of Complexity

Stephen Hawking predicted that the 21st century will be the "century of complexity." Now that most laws of the universe have been discovered, scientists and engineers must attempt to tackle problems that aren't easily answered with a formula [4]. For example, the Grand Challenges for Engineering for the next century include problems like engineering better medicines, making solar energy more economical, and providing energy from fusion [5]. These problems don't have an answer in the back of a textbook, so they require students to be able to think in global, multidisciplinary, and entrepreneurial contexts [5]. These problems have multiple components that all must be considered in order to develop a solution. There are many relationships between elements, including some that are nonlinear and some that are not predictable at all. These characteristics are often referred to as complexity [6].

Complexity can be understood using the Cynefin Framework shown in Figure 1. The framework can be broken up into four domains: simple, complicated, complex, and chaotic. Things in the simple domain are consistent. The cause and effect relationships between components are predictable and repeatable. The complicated domain similarly has predictable cause and effect relationships, but understanding them requires a domain expert. The complex domain has much more intertwined interactions that cannot easily be predicted or understood. These interactions can be measured and patterns can be found to gain a better understanding of the system, but those patterns might not hold true in the future. Finally, the chaotic domain has no cause and effect relationships, meaning virtually no information can be gained from the system [7].

Most engineering education builds knowledge and skills in the simple domain and then moves to the complicated domain. Students still need to have a deep understanding of the content, but most of the problems have a right answer. Some opportunities exist to work in the complex domain such as capstone courses, project-based courses, or other experiential learning. However, many experts in engineering practice have asserted that students could be better prepared to work on complex problems [2].

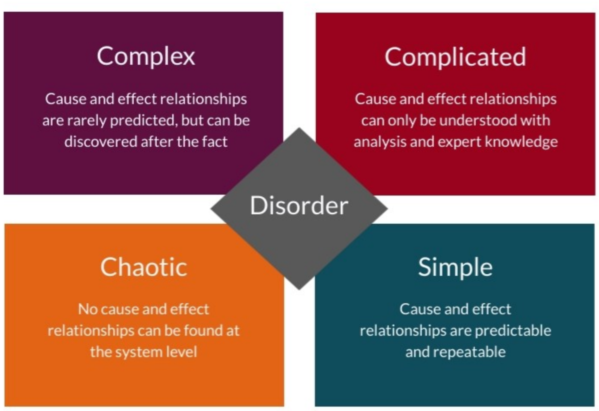

Fig. 1. The Cynefin Framework [7]

B. Complexity in the Context of Learning Frameworks

Learning frameworks can also be used to better understand complexity in the context of education. Both Bloom's Revised Taxonomy of Learning and Webb's Depth of Knowledge have been explored in the context of complexity.

Bloom's Revised Taxonomy of Learning (shown in Figure 2) is broken up into six levels of learning: memorizing, understanding, applying, analyzing, evaluating, and creating [8]. The memorizing level can be demonstrated by activities like defining, reproducing, and listing. Understanding goes a step further and includes actions like describing, explaining, and extrapolating. The application level involves skills such as implementing, demonstrating, and calculating. Analysis can be demonstrated by comparing, contrasting, and examining. Evaluating includes activities like judging, defending, and assessing. Finally, the top level of creating can be demonstrated by constructing, designing, and developing [9].

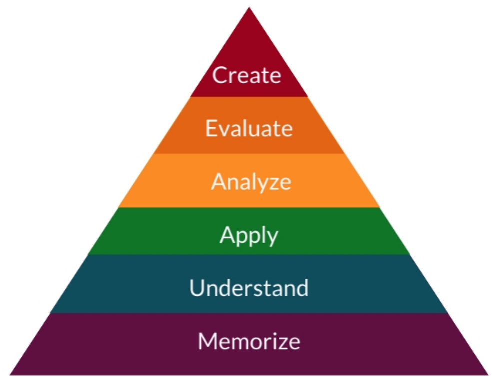

Fig. 2. Bloom's Revised Taxonomy of Learning [8]

Webb's Depth of Knowledge (shown in Figure [10]) is broken up into four levels: recalling and reproducing, applying basic knowledge and skills, thinking strategically, and thinking extensively [10]. DK1: Recalling and reproducing is a student's ability to remember definitions, formulas, and simple processes and procedures. All of the information they need to complete the task has already been provided to them. For DK2: Applying basic knowledge and skills, students are describing, explaining, and interpreting information. No complex reasoning is needed to answer these questions, but it does require students to take more than one step to solve the problem. DK3: Thinking strategically requires reasoning and planning. Students working in DK3 are solving non-routine problems and proposing solutions to problems. Rather than just being able to explain a relationship, they are backing their explanations up with evidence and application of knowledge. DK3 is mapped to the complicated domain. For DK4: Thinking extensively, students are relating multiple big variables and concepts in order to understand a topic at a deep level. Students must weigh options in order to decide the best way to approach the problem and make multiple decisions during their learning process. DK4 is mapped to the complex domain [10].

III. Student Clustering

Many expert teachers are able to observe students and recognize who is on track for success when they are in the simple or complicated domains. However, this becomes more

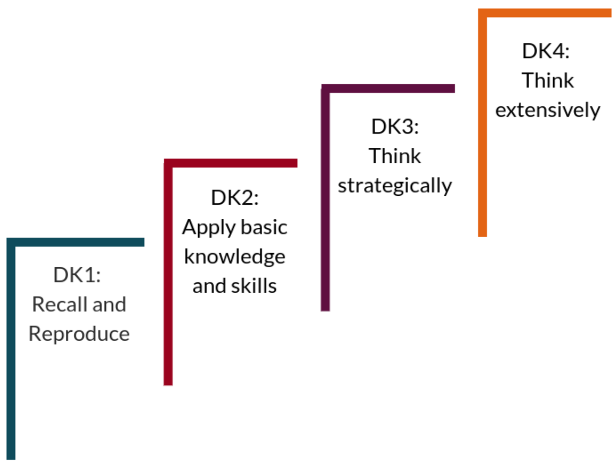

Fig. 3. Webb's Depth of Knowledge [10]

challenging when students are working the in the complex domain where the answers they are working towards have not yet been solved. However, educational data mining and machine learning may be the key to finding patterns and predicting student success in the complex domain.

Machine learning methods can be broken up into two main categories: supervised and unsupervised learning. Supervised learning means that all data are labeled before the algorithm is applied (e.g. labeling students as high- or low-performing and feeding that information to the algorithm). Unsupervised learning, on the other hand, does not start with labeled data points [11]. For example, in the case of clustering, the algorithm finds which points are most closely related and forms groups accordingly. The benefit of using an unsupervised method is that it might find patterns that a human may not have considered or noticed. This can be especially helpful in open-ended learning environments where students have a high degree of autonomy and can navigate the course in different ways [12]. This freedom can make it difficult for instructors to find patterns among students, but using clustering and other unsupervised methods can help uncover trends [13], [14].

Within Educational Data Mining (EDM), clustering can be used to group both similar course resources and students [15]. Common clustering applications include making personalized recommendations, detecting undesirable student behaviors, putting students into groups, constructing personalized coursework, and student modeling [16]. Clustering can be a powerful tool in educational data mining because it can be used even in complex learning environments [17], interactive modeling environments [18], [19], and collaborative problem solving environments [20]. The ability to handle complex data makes clustering a promising choice for analyzing Innovation-Based Learning data.

IV. Methods

A. Cardiovascular Engineering Course

Student data was collected during an offering of Cardiovascular Engineering, a cross-listed course at a medium-sized research university for both undergraduate and graduate students. Rather than being assessed with tests, homework, and quizzes, students were assessed on their ability to apply what they were learning in class to an innovation project [21]. Students explored funding opportunity announcements to find ideas for projects and formed groups around shared project choices [22]. Success was measured by the amount of external value created by each project group. External value consists of two main components: providing value outside of the classroom and getting external review. For example, presenting a peer-reviewed poster would be high external value because the poster is contributing to the scientific community outside the course and it gets external review during the peer-review process.

Class time was spent clarifying course content and providing learning updates where students could get feedback on their project and learning objectives [23]. Students used a custom learning management system that gave them access to pertinent resources [24] and allowed them to log progress on their learning objectives and deliverables [25]. An example of a learning objective and corresponding deliverables as logged in the portal can be found in Figure 4.

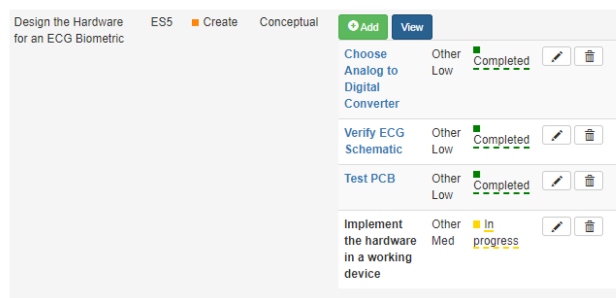

Fig. 4. An example learning objective and corresponding deliverables from the course. Students tracked learning objectives and deliverables in an online portal where they could upload titles, descriptions, and categories for each entry.

B. Dataset

28 students agreed to participate in the study: 13 undergraduate seniors, 3 Masters students, and 11 PhD Students (1 student did not provide a program level). 22 students were male and 6 were female, and the mean age was 26.5. A variety of majors and programs were also represented in the sample; 9 students were in Biomedical Engineering, 9 in Electrical Engineering, 5 in Mechanical Engineering, 4 in Computer Engineering and 1 in Health, Nutrition, and Exercise Science. On average, students ended the semester with 8 learning objectives and 32 deliverables, but many students had other learning objectives and deliverables that were deleted or adjusted during the semester. The dataset for each student included all of the text that they typed into the portal including learning objective titles and descriptions and deliverable titles and descriptions. Students grouped their learning objectives into categories, but these categories were not included in the

text data because categories could be interpreted differently across students.

C. Clustering

Using the scikit-learn library in Python [26], all the words that students wrote in their learning objectives and deliverables were tokenized and counted. The cosine similarity was then calculated to compare each student with every other student. Agglomerative clustering was then performed on the cosine similarities. By looking at the output in Figure 5, it was clear that four main clusters emerged.

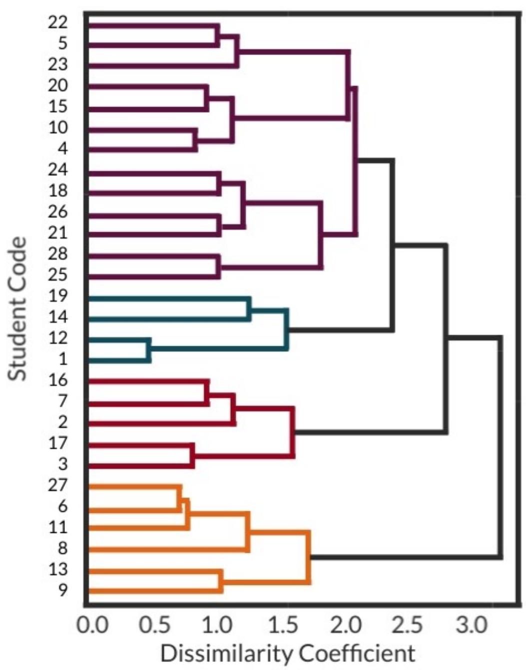

Fig. 5. A dendrogram showing the hierarchical agglomerative clustering performed on the students. Each branch represents a student. Students that are connected by a branch are most closely related, and the lower the dissimilarity coefficient of a connection, the closer they are related. For example, students 1 and 12 are most closely related because their branches connect at a dissimilarity coefficient of about 0.5. From the dendrogram, it was clear that 4 main clusters emerged from the data. Each of the clusters is colored to help visualize the natural breaks in clusters.

D. Mapping Student Trajectory

After each of the students had been placed into a cluster, a support vector machine classification model was trained to predict which cluster a new student would fall into. Data for each student was then broken up by day, and the cluster was predicted for each student over time. For example, the dataset for a student on Day 50 would include all the learning objectives and deliverables they had added by Day 50, but none of the data following Day 50. Each student's cluster can then be mapped over time in order to see if and how clusters change.

E. Extracting Most Pertinent Features

Using the classification model, Chi-Square was calculated for each word, showing which words are more likely to differentiate between classes. The greater the Chi-Square value, the greater dependence on classification, meaning that word is a strong differentiator. Words with the highest Chi-Square values were then sorted into their associated cluster. These words along with analysis of each cluster contributed to the naming of each cluster.

F. Comparing with Instructor Observations

After the clusters had been formed and named, the descriptions of each cluster were given to two of the instructors. These descriptions can be found in Table 1. The instructors then individually grouped the students into clusters based off of their own observations. They then both came together to discuss any students that they disagreed on and came to a final decision about all students. Their results were then compared with the clustering algorithm's results. The inter-rater reliability was calculated by finding Cohen's Weighted Kappa. Cohen's Weighted Kappa was chosen because it accounts for ordered categories. For example, a mismatch of Learner and Innovator would be weighted as a closer match than a mismatch of Surface Level and Innovator. Finally, the instructors were given the algorithm's groupings and were asked about any discrepancies in order to learn why discrepancies may have occurred.

TABLE I
CLUSTER DESCRIPTIONS

Name	Description
Surface Level	Compiled some information about a topic but got little to no review and did not reach any audience
Surveyor	Explored and summarized existing information about a topic and compiled it to share with others
Learner	Worked to become a subject matter expert in a specific area and applied that expertise to a problem
Innovator	Used the engineering design process to develop a new and unique solution to a problem

V. RESULTS

A. Clustering Results

Four clusters emerged from the data, and they were later named based off of the words that differentiated them from the other clusters. More information about how the clusters were named can be found in subsection *C*. Of the 28 students, 13 were classified as Innovators, 5 were classified as Learners, 4 were classified as Surveyors, and 6 were classified as Surface Level. Figure 6 shows what clusters top performing and lower performing students fell into, and Figure 7 shows the cluster breakdown by year in school.

All Innovators were considered top performing students, meaning they had a high external value deliverable by the end of the semester. All Surface Level students were considered lower performing students. 4 of the 5 Learners were considered top performing students; the 5th did not complete any of their planned deliverables.

Undergraduate seniors fell into all 4 of the cluster categories; 6 were Surface Level, 3 were Surveyors, 3 were Learners, and 1 was an Innovator. Graduate students only fell into the Learner and Innovator categories; 12 were Innovators and 2 were Learners. 1 student did not provide a year in school, so that student was omitted from Figure 7.

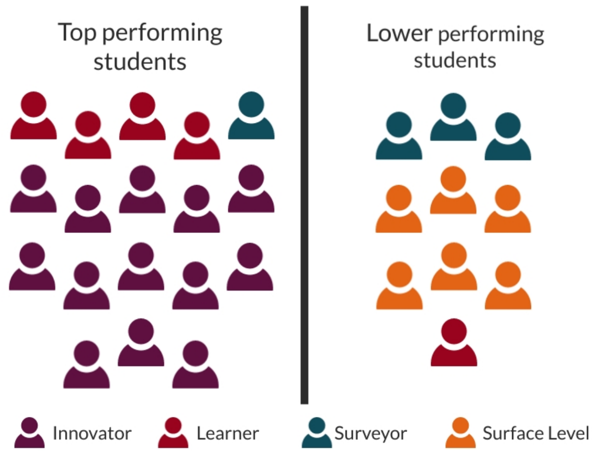

Fig. 6. The number of students in each cluster in relation to their performance in the class. Top performing students were students that had a high external value deliverable during the course of the semester (e.g. peer-reviewed publication or presentation, invention disclosure, etc.

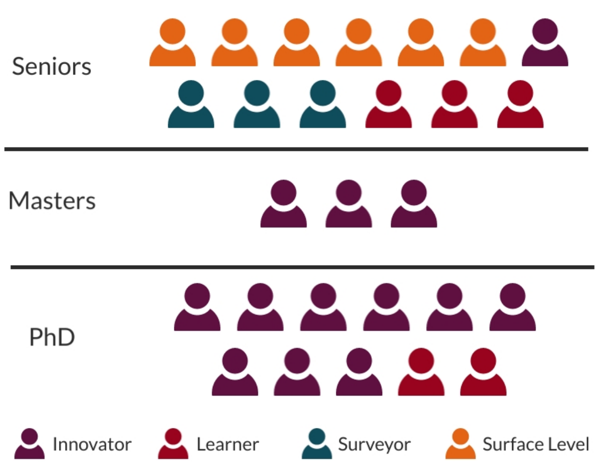

Fig. 7. The number of students in each cluster in relation to their status in school.

B. Student Trajectory Results

The cluster trajectory for each student was mapped as shown in Figure 8. At the beginning of the semester, there was not enough logged information to group the students. By the third week, many students were starting to log learning objectives and deliverables to prepare for their first group in-class presentation. By the time of the presentation, about half of the students were already grouped into the cluster that they would stay in for the rest of the semester. By the halfway point of the semester, all but one student was classified into their final cluster.

Many of the groups had members that all ended up in the same cluster, and almost all groups had members that were either consistently high performers or consistently low performers. Only Group D had 3 members that were low performers and 1 member that was a high performer.

C. Extracting Most Pertinent Features Results

The Innovator cluster was differentiated by their use of the words *application, knowledge, analysis, data, symposium, literature, create, processing,* and *patent*. These words are tied closely to the high external value deliverables that the students created or the engineering design process, giving us the name of this cluster. The Learner cluster was differentiated by their use of the words *learning, course, concepts, study,* and *pitch*. Most of the Learners focused on learning the course content as well as completing online courses related to their topic. *Pitch* was a popular word because some of the Learners competed in a business pitch competition which was often discussed in their learning objective and deliverable logging. The name for this cluster came directly from the presence of the word *learning*. The top words for Surveyors were *presentation, paper, research,* and *writing*. These students focused on reviewing and summarizing existing knowledge about a particular area and sharing it both through presentations and a research paper. Although the word *survey* did not appear in this cluster's learning objectives, the name was chosen to differentiate this group from those doing scientific research. The Surface Level cluster was differentiated by their use of the words *website, video, layout, analysis,* and, most strongly, *information*. These students found information about a topic and created websites or videos to compile their work. These students did not dive deep into their topic and did not share their learning more broadly, giving this cluster the Surface Level name. The words that differentiated most between each cluster appear in Figure 9.

D. Comparing with Instructor Observations

Figure 10 shows how the instructor and algorithm classifications compare. The shaded diagonal represents cases where the algorithm and instructor classifications match. 18 of the 27 classifications matched (the student that did not complete any deliverables was not included in this chart because the instructors agreed there was not enough information to classify that student). The weighted Kappa between the algorithm and the instructors was 0.608. Kohen's Weighted Kappa of 0 means random agreement and Kappa of 1 means perfect agreement. Although there is no firmly agreed upon appropriate ranges of Kappa, 0.608 is considered moderate agreement by most experts [27].

After instructor interviews were completed and the mismatches were analyzed, it became clear that discrepancies occurred for two main reasons: 1) difficulties recognizing and classifying a Learner, and 2) the algorithm's inability to tell quality of work. Reason 1 led to 7 differences in classification,

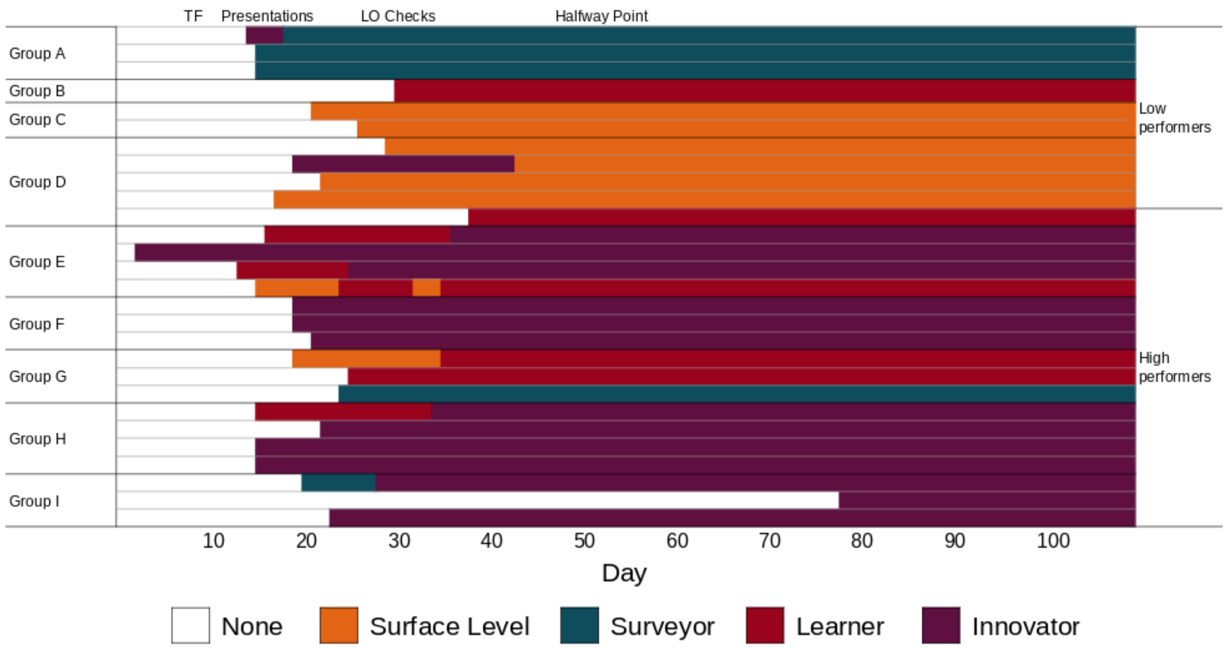

Fig. 8. Student trajectory through the course. Each row corresponds to a different student, and students are grouped based off of their teams and their success in the course. Various milestones are marked at the top of the figure including team formation (TF), the 1st presentations that teams gave (Presentations), the first learning objective checks (LO Checks), and the midpoint in the semester (Halfway Point).

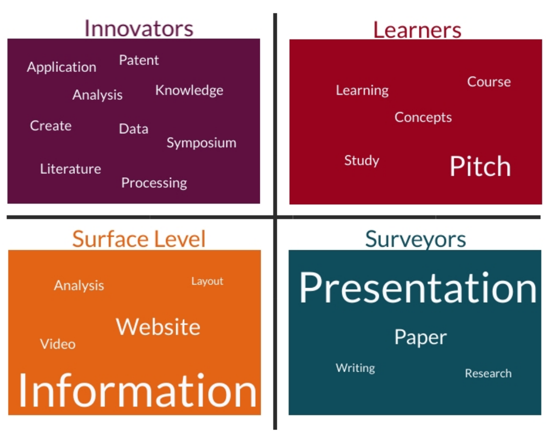

Fig. 9. The top words that differentiated between each cluster. Larger words had larger Chi-Square values, meaning they more strongly differentiate students in that cluster from students in other clusters.

and reason 2 led to 2 differences in classification. Difficulties in recognizing and classifying Learners may have occurred because of the ambiguity of the word *learning*. It is hard to differentiate Surveyors from Learners because of the difficulty in comparing lower level and higher level learning, and it is hard to differentiate Learners from Innovators because the deliverables for both Learners and Innovators look similar. This problem also occurs when differentiating Webb's DK3: Thinking Strategically from Webb's DK2: Apply basic knowledge and skills and DK4: Thinking extensively [10].

The algorithm's inability to tell quality of work caused 2 students to be classified as Innovators by the algorithm and Surface Level by the instructors. Although the students were writing about the right things, they did not perform at the level that the instructors expected of them.

		Instructor Classifcations			
		Surface Level	Surveyor	Learner	Innovator
Algorithm Classifications	Surface Level	5		1	
	Surveyor		2	2	
	Learner			1	3
	Innovator	2		1	10

Fig. 10. Comparison of algorithm classification and instructors classification. The number in each box is the number of students that fell into that classification. The shaded boxes along the diagonal represent matches between the algorithm and the instructors. Non-shaded boxes are mismatches between the algorithm and the instructors.

VI. Discussion

A. Cluster Descriptions and Examples

By looking at the top words that differentiated between each cluster and looking more closely at each student's learning objectives and deliverables, we were able to understand more about each cluster and map them to the Cynefin framework, Bloom's Taxonomy of Learning, and Webb's Depth of Knowledge. This mapping is shown in Figure 11.

Cluster Name	Surface Level	Surveyors	Learners		Innovators	
Cynefin Framework	Chaotic	Simple	Complicated		Complex	
Bloom's Taxonomy of Learning	Memorize	Understand	Apply	Analyze	Evaluate	Create
Webb's Depth of Knowledge	DK1: Recalling and reproducing	DK2: Applying basic knowledge and skills	DK3: Thinking strategically		DK4: Thinking extesnively	

Fig. 11. Clusters and their mapping to the Cynefin Framework, Bloom's Taxonomy of Learning, and Webb's Depth of Knowledge.

- *Surface Level*: Surface Level students compiled some information about a topic but did not reach an audience or get review on their work. These students are are mapped to the chaotic domain because they were not able to define the bounds they were working within. Students in this cluster started with innovative ideas, but eventually decided to create websites and videos that summarized existing resources. These deliverables were not classified as high impact because the videos and websites had little to no visits or reviews. Rather than focusing on learning and gaining knowledge, these students focused on collecting information, mapping them to Webb's DK1: recalling and reproducing. For Bloom's Taxonomy, these learners fall somewhere between memorizing and understanding; their deliverables show that they were able to reiterate existing information, but they do not show direct evidence of understanding. An example of a group of students that fell into this cluster was one that chose a topic, read a handful of resources, and put the information they read onto a website.
- *Surveyor*: Surveyors explored and summarized existing information about a topic and compiled it to share with others. They are mapped to the simple domain because they are not exploring beyond existing knowledge. It is important to note that the Surveyor cluster is not performing original scientific research. Rather, they are reviewing and summarizing existing work in order to share it with a wide range of audiences. The main difference between this group and the Surface Level cluster is that these students dug deeper into their topic and made an effort to share their work with others, mapping them to Webb's DK2: applying basic knowledge and skills. Because they were able to share their work for a variety of audiences and contexts, they showed evidence of achieving the Understanding level of Bloom's. An example of a group with students in this category was one that chose a broad topic, reviewed existing resources, and gave a presentation about their findings. This differed from the website because the students had to explain their content and answer questions.
- *Learner*: Learners are mapped to the complicated domain because they became content experts in a specific area. Learners differ from Surveyors because the Learners dive deep into one topic rather than learning about something more broadly. These students reached Webb's DK3: thinking strategically because they used their learning to solve a problem. In addition, they have applied their new skills and knowledge to make contributions to the field, mapping them to the Bloom's Apply and Analyze levels. Most of the students in the Learner cluster did show an ability to innovate, but they rooted their work more deeply in their learning. Some of the students that fell into this cluster worked on a project where they used an Application Programming Interface (API) to add new features to an existing system. They added new value to the system, but they could use existing resources to work step-by-step through the project.
- *Innovator*: Innovators are mapped to the complex domain because they are working on projects that have no clear answer. In order to work in this domain, the students must be able to devise a solution, test it, and use the information gained to improve the solution. Having an expert understanding alone cannot lead to a perfect solution. Rather, Innovators must come at the problem from multiple ways to better understand the project and improve a solution, mapping them to Webb's DK4: thinking extensively. Innovators reach the Bloom's levels of Evaluate and Create because they are evaluating potential solutions in order to better understand the problem and create a new one. An example of a group of Innovators worked on a new wearable sensor. The students needed to combine knowledge from multiple areas in order to create a product.

B. Insights Gained

By exploring the breakdown of clusters, it is clear that Innovators and Learners were more likely to complete a high external value deliverable during the course. In addition, all Surveyors and Surface Level students were undergraduates. This illustrates that undergraduate students might need additional support to grow into Learners or Innovators. The three undergraduate Learners and one undergraduate Innovator all were in groups that had both undergraduate and graduate students, potentially adding to their success. In the future, it may be wise to encourage more groups that mix both undergraduate and graduate students together to help foster growth.

From the trajectory results, we see that it is possible for students to switch to a different cluster during the semester, especially if the majority of their team is in that cluster. Because it is possible to switch clusters, the instructor can play a role in providing guidance for students in the Surface Level and Surveyor clusters. By being able to categorize students (either by observation or by using the trained classifier), instructors can try to better guide students into the Learner or Innovator clusters.

The trajectory results also illustrate the importance of providing student feedback early and often during the semester. By the midpoint in the semester, most students were already settled into the cluster they would stay in. Rather than waiting until later in the semester, instructors should try to provide a formal review sometime during the second quarter of the semester to ensure the students have time to adjust their plans if needed.

C. Limitations

Two of the major limitations of this work are the algorithm's inability to understand the context of words and its inability to understand the quality of the deliverables being created. For example, if a student uses the word *research* in their learning objectives, the algorithm cannot tell the difference between *survey and summarize research* and *scientific research*. Similarly, if a student has a firm understanding of the process of the class and is able to write learning objectives and deliverables that have clear high external value, the algorithm will not be able to tell if a student is actually creating high quality work. Therefore, this tool is not designed to take the place of instructor review, but rather to supplement it.

In addition, because this data is only from one semester, the developed clusters and classifier model may not perform similarly in future semesters. Therefore, the goal is not to develop one perfect model, but rather continue to explore how the model might change over time. Important insights into improving engineering education may be found by looking into these changes.

D. Future Work

As more data is collected, we can explore how the clusters evolve or if any new clusters emerge. It might also be possible to better understand student trajectory and what sorts of pathways allow students to move from less successful clusters to more successful clusters. If patterns emerge, instructors may be able to suggest specific actions that can help students transition to the Learner or Innovator clusters. Similarly, these patterns may show how team composition effects student clusters. If we have a better understanding of these interactions, teams could potentially be adjusted in order to maximize group success.

In addition, more work can be done to dive deeper into individual students. For example, it might be insightful to do an interview with a student that switches clusters during the semester to see if they had any changes in attitude, understanding of the course, group dynamics, etc.

VII. Conclusion

Clustering students by using their learning objective data provides new insights about how students navigate an Innovation-Based Learning course. Four main clusters emerged from this data set: Surface Level, Surveyors, Learners, and Innovators, each with their own words that differentiate them from other clusters. Students can switch clusters during the semester, and many of those switches seem to be related to group behavior. This work could lead to better understanding of how students innovate and solve problems, allowing for advancements in personalized education, group matchmaking, and even assessment. By implementing these tools, these education models can be scaled up, allowing more students to grow in their ability to work within the complex domain. They develop problem solving, adaptability, and creativity, helping them tackle big problems and become an Engineer of 2020.

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