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Teaching artificial intelligence and machine learning to materials engineering students through plastic 3D printing

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Abstract

Computational tools in conjunction with Artificial Intelligence (AI) and Machine Learning (ML) have the potential to play significant roles in the future of Materials Science and Engineering (MS&E). These concepts need to be introduced to students throughout existing MS&E curricula. There is currently a lack of datasets and tools that are appropriate for introducing the complex topics of AI and ML to engineering students with little to no knowledge of computer science or programming. In this paper, we report on the background, development, and application of a new 3D printed plastic dataset and related active learning exercise. This exercise was performed on a relatively new "no-code" software platform (developed by Citrine Informatics) that uses AI and ML to solve real-world materials engineering problems. Our approach places an emphasis on the importance of materials engineering domain knowledge and structured material data for the successful application of AI and ML in solving materials engineering problems. Student perceptions of the approach and its outcomes were shown to be largely positive. In particular, the exercise was shown to enable students to understand the role of AI and ML in MS&E problem solving. The implications of this work are to share our efforts and findings with educators, to get feedback and to inspire ideas for teaching AI and ML to engineering students without a programming background.

Introduction

Many new and existing companies are starting to adopt AI and ML software that users with variable computer programming competency can apply to gain a better understanding of their engineering problems and potential solutions [1,2]. This speaks to the increasing recognition that ML functions, algorithms, and software packages should not be restricted to only those who understand the advanced mathematics and programming involved in creating AI and ML tools. MS&E graduates may encounter these tools in their career in the same way that they could expect to encounter physics-based simulation tools, such as finite element modelling software packages.

There has been some work done to assess AI literacy independent of programming fluency. Adoption of AI and ML resources have been created in many fields where programming fluency is not typically associated, such as medicine [3,4] and business [5]. There is even some work exploring early adoption in precollege education such as the AI4K12 initiative that promotes AI literacy for students before they enter higher education. Specifically, Laupichler et al. and Hornberger et al. [6-8] developed assessments that include questions ranging from 'Name examples of technical applications that are supported by artificial intelligence' to 'Give a short overview about the history of artificial intelligence'.

In this work we describe an active learning framework where students design, manufacture, and test to create robust process-structure-properties linkages of 3D printed materials. We aim to explore these aspects using a novel 'design-driven' approach (Figure 1) that emphasizes the use of software interfaces that do not require computer programming skills to solve engineering problems with AI and ML. This approach is in contrast to existing approaches which emphasize computer science and programming through pre-requisite classes throughout the curriculum.

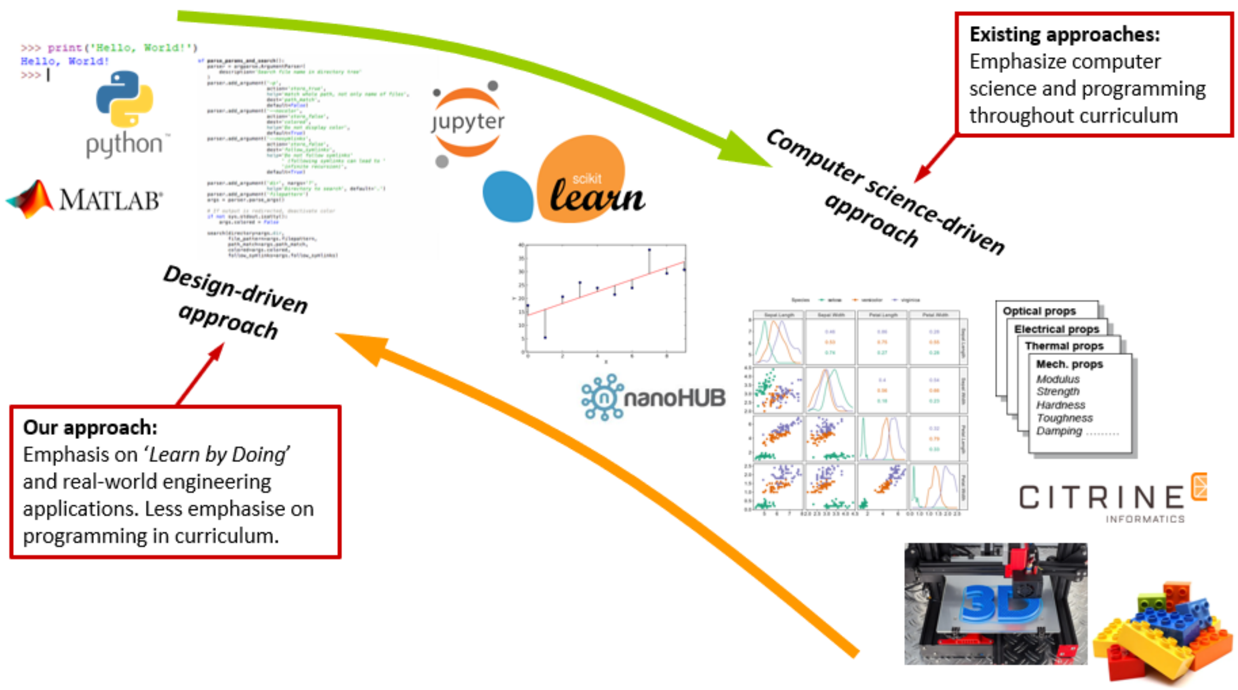


Figure 1: Approaches to AI and ML teaching in the context of materials engineering.

Curricula

This exercise is developed for a relatively new core course (MATE 245) in the MS&E program at California Polytechnic (Cal Poly) State University, San Luis Obispo. The objective of the course is to introduce sophomore students to quantitative and qualitative analysis methods and tools used in Materials Engineering. For example, MATE 245 students are introduced to statistics for experiments, data mining, data visualization, regression analysis, numerical integration, Weibull analysis, quantitative image analysis and ML. In alignment with Cal Poly's *Learn by Doing* philosophy, a strong emphasis of the course has been placed on real-world engineering problems using materials data. A significant part of the raison d'être of this course was an avenue to integrate the emerging topics of AI and ML into the MS&E curriculum at Cal Poly. The majority of the students taking this course have little to no knowledge of computer science, computer programming (e.g., Matlab or Python), or algorithm development. This presents an opportunity to be innovative in the approach taken to introduce the topics of AI and ML.

At present, one week (3 hours lab time) is devoted to exploring the concepts of AI and ML. Cal Poly transitioning from quarters to semesters will expand this approach in the future to two – three weeks (6-9 hours lab time), allowing for more meaningful exploration of these topics.

Methods

Overview

The aim of the exercise is to expose MATE 245 students to AI and ML through an iterative activity that involves development and curation of a material and process property dataset of 3D printed plastics. An overview of the process is shown in Figure 2. Students begin by collecting and organizing plastic filament data from published literature and from an existing dataset provided by the instructor. After data structuring and curation, the data can then be ingested to train a ML model. Next, the ML model is used to perform Design of Experiments (DoE), generating new possible experiments (material and 3D printing process combinations) based on a specified design space. Students apply their MS&E domain knowledge when defining the design space of the new possible experiments and when they prioritize candidates for further exploration. The newly generated data can be fed back into the AI model, allowing students to 'close-the-loop' on the material design and process optimization procedure. The key steps of this iterative process are further described in the subsequent sections of this paper.

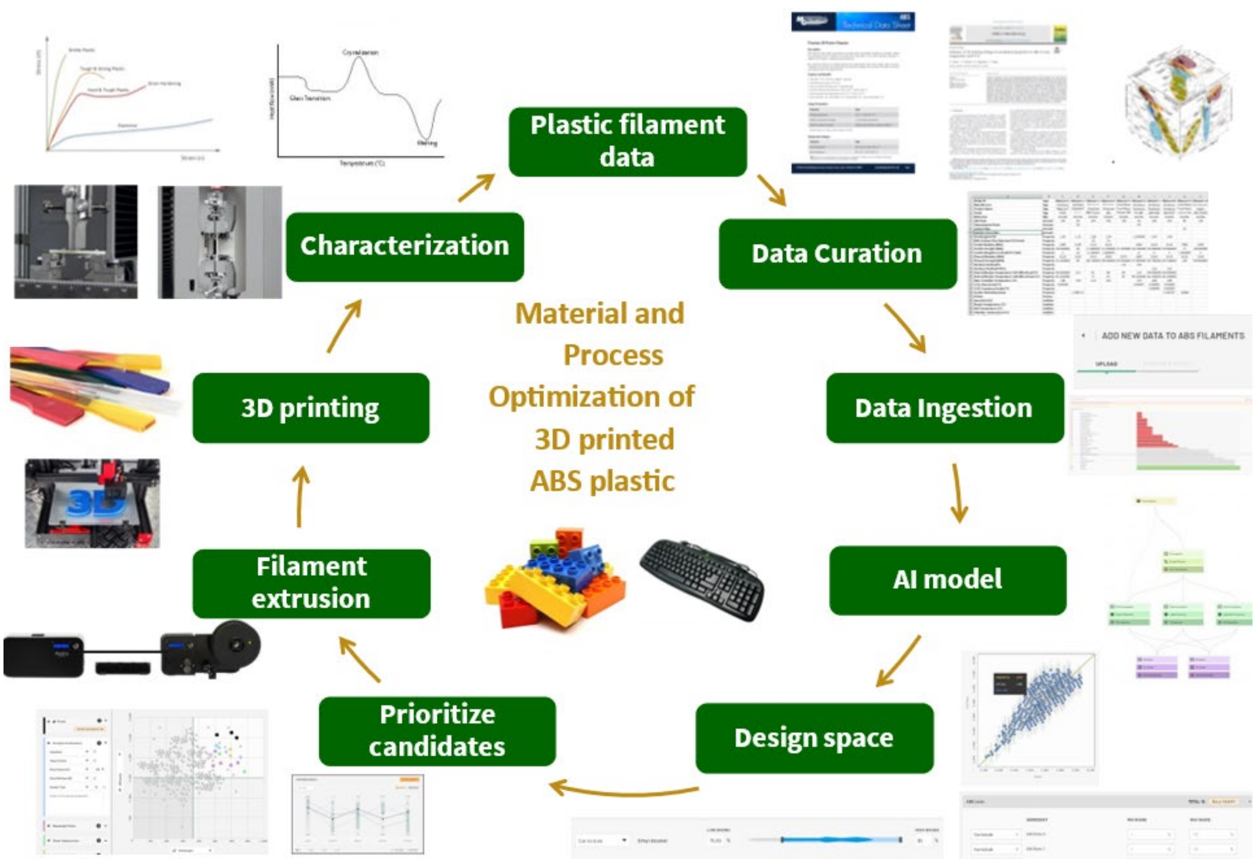


Figure 2: An overview of material and process optimization exercise for 3D printed plastic. The closed-loop nature of the exercise allows students to thoroughly investigate the application of ML to MS&E and its potential benefits and shortcomings.

ABS Plastic 3D printed dataset and material characterization

Students explore the optimization of ABS (Acrylonitrile Butadiene Styrene) 3D printing filament, which is a popular choice for 3D printing due to its temperature resistance, strength, and processability. The two areas of investigation for optimization include the ABS formulation and various 3D printing process parameters (Table 1). In the material formulation, different types of reinforcing fibers (carbon, glass, aramid) at different fiber volume fractions are considered. The 3D printing process variables under investigation include nozzle temperature, print speed, and layer height thickness (also known as z-offset). This initial dataset is currently being expanded to include a wider variety of popular off-the-shelf plastic 3D printing filaments (presented in Appendix 1). There are a variety of process parameters listed in Appendix 2 that are kept constant in the creation of the dataset. Future iterations of this approach could include an optimization of the process parameters that have been kept constant, such as print infill geometry and print infill density. To date, students have worked with off-the-shelf filaments. Additional access to a filament extrusion system would allow students to synthesize new candidate materials (with new fiber volume fractions) proposed by the ML model. After printing, mechanical properties (such as tensile strength and modulus), thermal properties (such as glass transition temperature) and physical properties (density) are subsequently characterized in a materials lab class by the students.

Table 1: ABS material formulations and 3D printing processing parameters used in the creation of the dataset from off-the-shelf 3D printing filaments.

Polymer	**Fiber Type**	**Fiber v_f (%)**	**Bulk/Infill Print Speed (mm/s)**	**Layer Height or Z-offset (mm)**	**Nozzle Temp. (°C)**	**Bed Temp. (°C)**
ABS	None	N/A	90, 105, 120	0.1, 0.2, 0.3	210, 230, 250	100
ABS	CF	10, 20	90, 105, 120	0.1, 0.2, 0.3	220, 240, 260	110
ABS	GF	10, 20	90, 105, 120	0.1, 0.2, 0.3	220, 240, 260	105
ABS	Aramid	10, 20	90, 105, 120	0.1, 0.2, 0.3	240, 260, 280	100

Implementation of AI and ML in "no-code" software platform

The emerging prevalence of the Citrine Informatics [9] software tools in the materials engineering industry demonstrates its relevance to current undergraduate students who may encounter it or similar software tools in their careers. In particular, the cloud-based, enterprise-level Citrine Platform provides the capability to assess complex materials data, build machine learning (ML) models, and design experiments, all with a user-friendly "no-code" graphical user interface (GUI) accessible via any web browser. The software has been successfully applied to a variety of materials and chemicals development problems including superconductors, thermoelectrics, metal alloys, organic conductors, and colloids [10-14].

The workflow of the Citrine Platform GUI is based off a 'branch' workflow shown in Figure 3. The platform allows students to tweak ML parameters and see the effects of these changes in real time, making it an ideal tool for enhancing classroom interactivity and developing an intuition for how the ML “black box” functions, without in depth programming knowledge. The Citrine Platform’s unique ML-driven DoE capability provides a real-world application of ML to industry, which can enable students to understand and identify the characteristics of successful AI-driven product development projects. The ability for students to learn and perform an end-to-end data science workflow without writing a single line of code, all within the context of materials design, has the potential to enhance their educational experience but will also improve their employability in a rapidly advancing field.

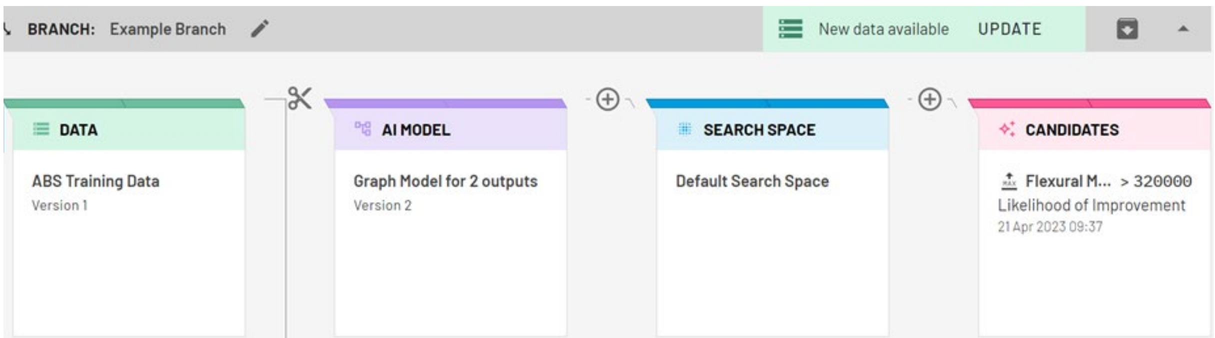


Figure 3: Citrine Platform ‘branched’ workflow for investigating materials development using AI/ML without the need for computer programming.

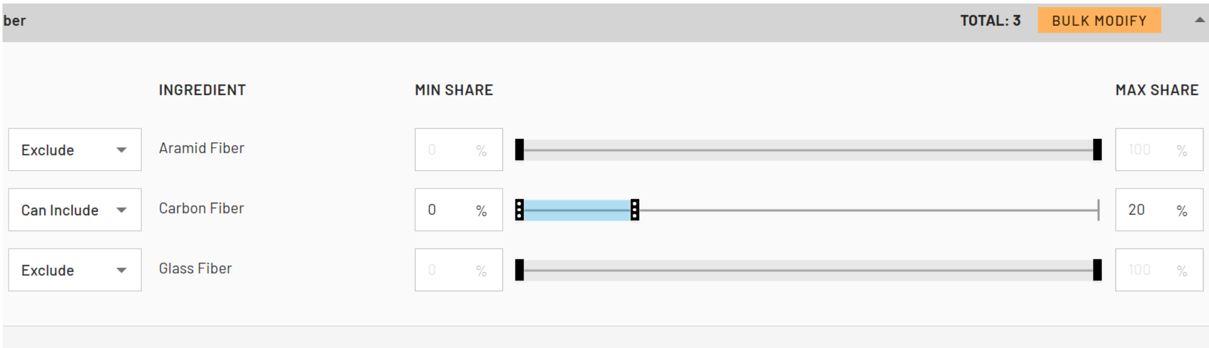
Following 3D printing and material characterization, students curate the material property dataset so that it can be ingested in the Citrine Platform to train a ML model. The output of this data curation step is a structured data table that has been organized in a predefined format (Table 2). This is a crucial step of the exercise as it exposes students to material property data curation, which is an essential part of creating meaningful ML models. After the curated dataset is ingested into the Citrine Platform, a ML model (random forest regression model) is generated by the platform. The AI model can be visualized in the Citrine Platform as a branched tree (Figure 4), which aids students understanding of the links within the model.

Table 2: A snapshot of a structured data table used to train a ML model in the Citrine Platform.

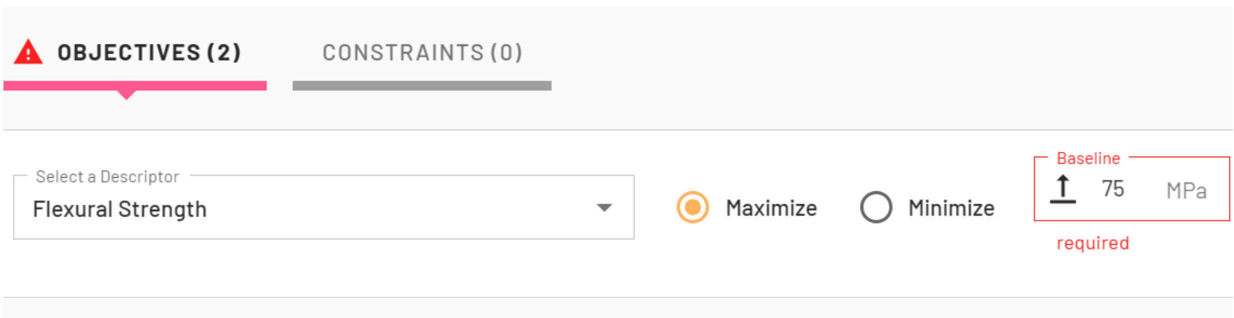
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	Recipe ID	Product Name	Printer	Nozzle Temperature (°C)	Layer Thickness (mm)	Speed (mm/s)	ABS Resin	Carbon Fiber	Glass Fiber	Aramid Fiber	Density (g/cm^3)	Tensile Modulus (MPa)	Tensile Strength (MPa)	Flexural Modulus (MPa)	Flexural Strength (MPa)	Glass Transi Temperatu (°C)
2	Type	Tags	Process	Condition	Condition	Condition	Amount	Amount	Amount	Amount	Property	Property	Property	Property	Property	Property
54	Specimen 52	ABS + CF	FDM	250	0.1	105	80.0	20.0			1.135	4606.5	47.6	5282.8	89.5	89.0
55	Specimen 53	ABS + CF	FDM	250	0.1	105	80.0	20.0			1.139	4638.5	45.2	5264.8	95.0	90.0
56	Specimen 54	ABS + CF	FDM	250	0.1	105	80.0	20.0			1.141	4631.0	44.9	5247.2	83.2	87.0
57	Specimen 55	ABS + CF	FDM	250	0.1	105	80.0	20.0			1.139	4593.6	48.6	5248.3	87.9	87.0
58	Specimen 56	ABS + CF	FDM	250	0.3	105	80.0	20.0			1.135	4595.5	43.3	5251.3	95.0	88.0
59	Specimen 57	ABS + CF	FDM	250	0.3	105	80.0	20.0			1.141	4567.7	45.0	5254.7	94.5	89.0
60	Specimen 58	ABS + CF	FDM	250	0.3	105	80.0	20.0			1.143	4617.3	44.9	5244.7	84.8	91.0
61	Specimen 59	ABS + CF	FDM	250	0.3	105	80.0	20.0			1.138	4614.9	45.4	5239.6	90.8	90.0
62	Specimen 60	ABS + CF	FDM	250	0.3	105	80.0	20.0			1.139	4587.8	40.9	5263.4	86.9	90.0
63	Specimen 61	ABS + CF	FDM	250	0.2	120	80.0	20.0			1.139	4607.0	45.9	5245.3	88.8	91.0
64	Specimen 62	ABS + CF	FDM	250	0.2	120	80.0	20.0			1.140	4607.3	39.6	5243.5	90.6	88.0
65	Specimen 63	ABS + CF	FDM	250	0.2	120	80.0	20.0			1.140	4595.7	42.9	5254.7	89.4	91.0
66	Specimen 64	ABS + CF	FDM	250	0.2	120	80.0	20.0			1.140	4576.0	42.7	5252.0	87.0	87.0

Figure 4: Citrine Platform AI model tree automatically generated after data ingestion.

The next step is to define a search space within the bounds of the 3D printing exercise on realistic new candidate materials for the ML model to generate. The bounds allow restrictions on ingredients and processing parameters in the form of real, integer, and categorical values. For the ABS 3D printing filaments, ranges for ingredients (such as fiber reinforcement) can be assigned (Figure 5a) in defining the search space. Reasonable ranges of process parameters can also be defined to ensure accurate candidates. This includes setting processing limitations of the available 3D printing equipment. Objectives for candidate materials, such as maximizing a particular material property, can also be defined in the Citrine Platform (Figure 5b).



(a)



(b)

Figure 5: (a) Material formulation constraints and (b) candidate material objectives being applied in the Citrine Platform.

The Citrine Platform GUI allows students to tweak ML parameters and see the effects in real time through data visualization (Figure 6). The generated candidate materials show model predictions of how varied compositions and processing parameters might affect a given filament's properties and performance. A process known as ranking is performed to compare candidates in which the model quantifies the performance of each candidate under a certain criterion. The two main scoring criteria include exploitation (highest performance) and exploration (highest uncertainty). The exploration criteria is useful in creating a more holistic dataset to improve the fit of the ML model. The third scoring criterion combines exploitation and exploration in a balanced ranking of candidates. After the ranking and prioritization of newly generated candidate materials, specific candidates can be explored further. The compositions and processing parameters for candidates of interest can be documented, 3D printed, and subsequently characterized. The newly obtained data can then be combined with the existing dataset and the loop of ML-driven DoE can be closed and repeated.

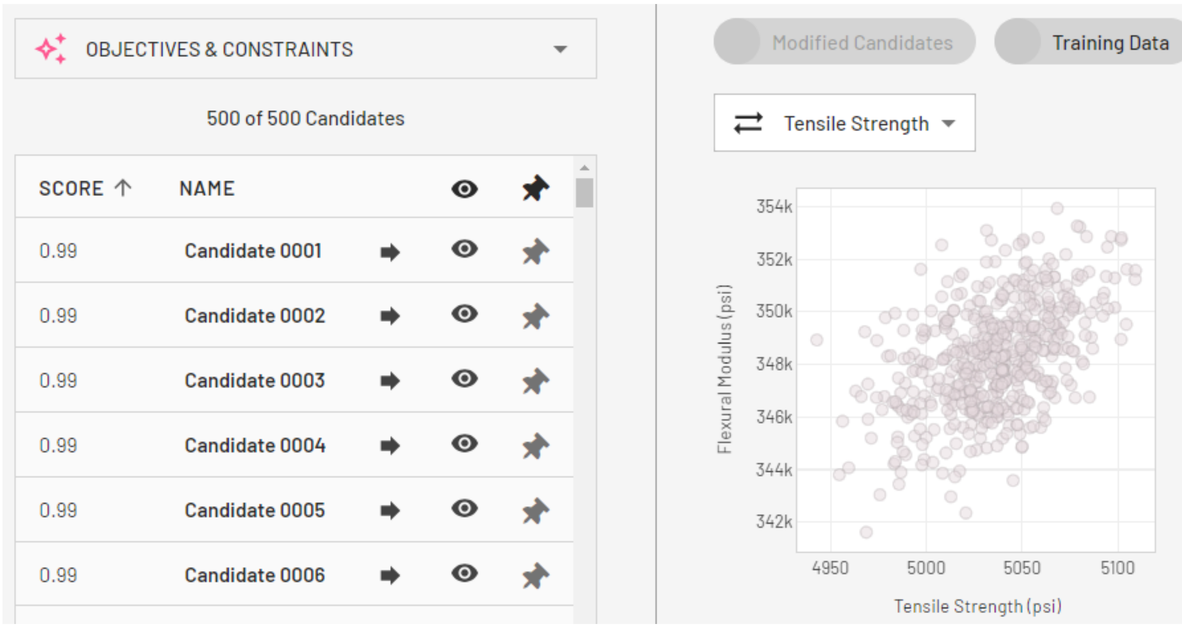


Figure 6: Visualization and prioritization of candidate materials generated by ML in the Citrine Platform.

The approach utilized here introduces students to applications of machine learning in an authentic way, connecting AI tools to physical samples and literature based as well as student-generated data. In working to build and analyze the data set, students develop both experimental skills and an appreciation for advanced computational methods.

Pilot Data Collection

Pilot quantitative and qualitative data have been collected to better understand the impact of the described activity on student perceptions of ML. Sections of the MATE 245 class in 2022 and 2023 were introduced to AI and ML concepts via a similar case study on the Citrine Platform via an instructor facilitated interactive demonstration.

In 2022, the MATE 245 class (~20 second-year students) were introduced to AI and ML concepts via a similar case study on the Citrine Platform. The students were surveyed before and after class to gauge their general understanding ML as a tool for engineers. The students were asked the same set of questions before and after class, responding on a traditional 5-point Likert scale ranging from strongly disagree to strongly agree:

1. I understand what Machine Learning is.
2. I understand how Machine Learning could be applied to Materials Engineering.
3. I think Machine Learning can help solve real-world Materials Engineering problems.
4. I think I will need to use Machine Learning tools at some point in my career.

In 2023, the MATE 245 class (~20 sophomore students) was again surveyed after being exposed to AI and ML on the Citrine Platform. One additional question was added related to ChatGPT, which had risen to prevalence in that time.

5. I think I will need to use ChatGPT at some point in my career.

In addition to the MATE 245 class, in the summer of 2023, two undergraduate research students were employed to aid in the development of the plastic 3D printing dataset and case study. These students spent 8 weeks working on developing the 3D printing case study in the Citrine Platform. During this time the students gained more in-depth knowledge of AI and ML through guided and independent research. The students were invited to provide prompt-based written reflections on their understanding and perceptions of ML and how it might be applied to their future careers.

Preliminary Findings and Discussion

The student survey results for before class and after class are shown in Figures 7 and 8, respectively. The reflections from the summer undergraduate research students are shown in Appendix 3.

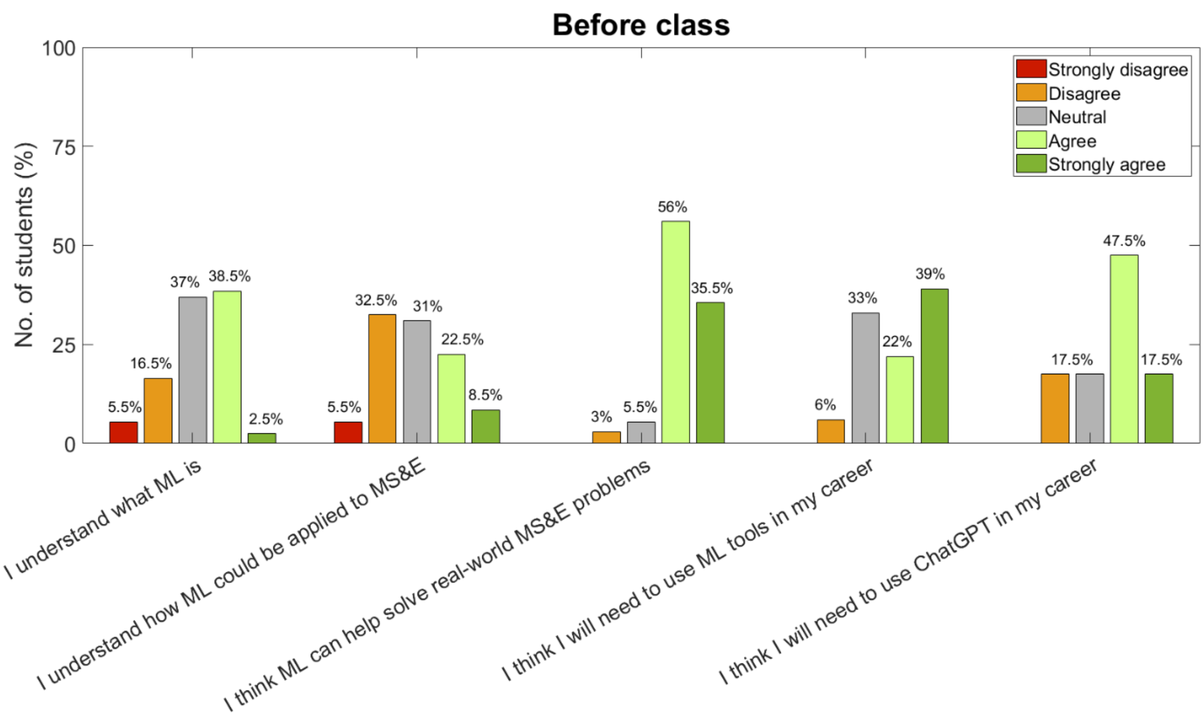


Figure 7: Students understanding of AI and ML and its relevance to MS&E before class, 2022 and 2023 surveys combined.

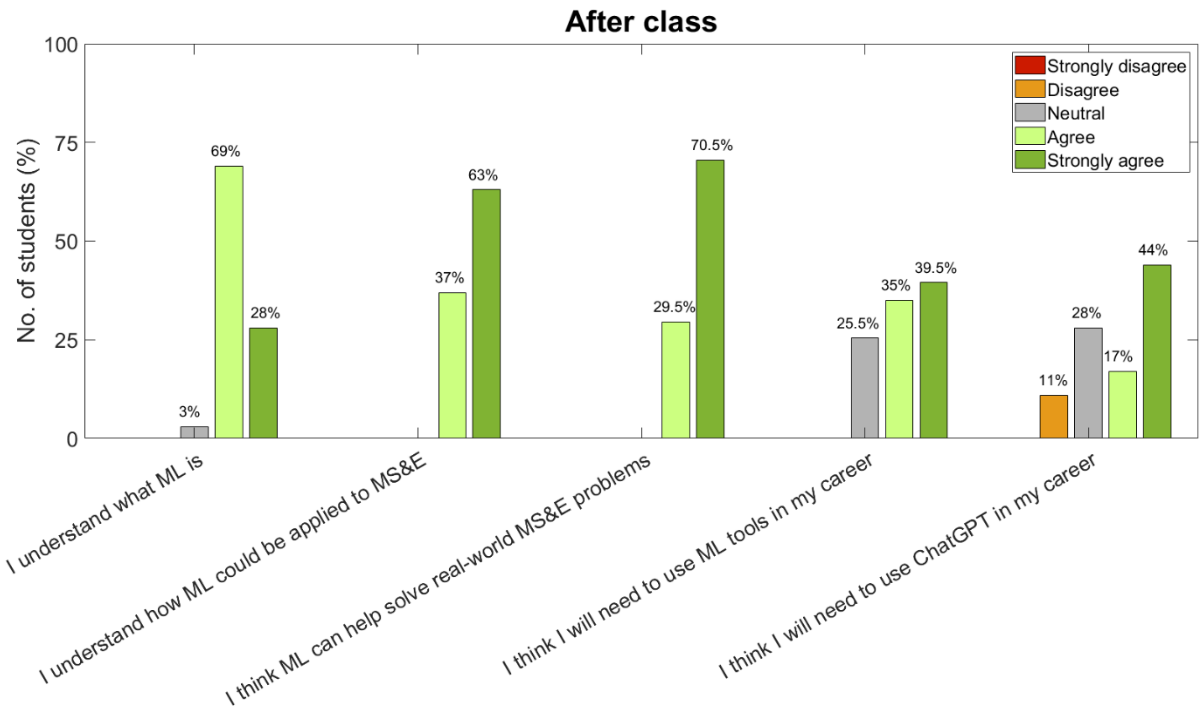


Figure 8: Students understanding of AI and ML and its relevance to MS&E after class, 2022 and 2023 surveys combined.

It is evident from the survey results in both years that exposure to the in-class case study resulted in general shifts in student perceptions about what ML is and how it can be applied to MS&E problem solving. Interestingly, the majority of students before class (in both years) indicated that they thought that ML could help solve real-world problems in MS&E and that they would need to use ML tools at some point in their career. They acknowledged a lack of understanding, however, of *how* ML could be applied to solve problems in MS&E. Following exposure through the case study example students reported an increase in both understanding of what ML is and how it can be applied to real world engineering problems.

The summer undergraduate research student reflections reported in Appendix 3 indicate a largely positive experience with the development of the 3D printing dataset and case study. Reflections indicate not only an improved awareness of the broad benefits of AI and ML in engineering, but an increased understanding of the critical steps (e.g. data structuring) of successfully applying ML to solve problems in MS&E. The student reflections allude to the students seeing themselves as consumers of machine learning tools (rather than developers) and this could have significant implications for future curricular developments. Both students shared a belief that they will likely need to use ML tools in their engineering and even non-engineering careers. One student (Student 1) expanded further to reflect that ML tools are still in their infancy and could become as important in engineering problem solving as Microsoft Excel.

The in-class students were only exposed to one specific engineering problem that could be solved with one specific AI and ML tool (i.e. the Citrine Platform). Because of this, their perceived benefit of AI and ML may be less than the two undergraduate research students who spent significantly longer working with AI and ML by applying a variety of software tools to a variety of materials engineering problems. Indeed, Student 1 remarked that “all fields of engineering also benefit from the increased abundance of ML, and those educated in how to apply it can solve a wide range of problems.” Similarly, the second undergraduate researcher (Student 2) remarked that they “believe machine learning will eventually work its way into many sectors and industries.”

Conclusions and Outlook

Exposing students to AI and ML concepts through a hands-on case study can help them identify how these concepts could be useful in MS&E and more broadly in their careers. The application of a “no-code” software, such as the cloud-based Citrine Platform, can help enable students without a coding background to understand the role of AI and ML in engineering problem solving. Student perceptions of the “no-code” software exercise were overwhelmingly positive based on responses to survey questions before and after class, which indicated the approach has meaningful benefits for student learning.

A significant portion of the case study exercise utilized in MATE 245 relied on direct instruction. Moving forward, we plan to develop guided-teaching resources so students can more easily engage with the exercise outside of the classroom. Guided-teaching resources are intended to assist in scaling the exercise presented in this paper from a small classroom of approximately 20 students to larger lecture courses.

Our preliminary results lead us to the current hypothesis that a “no-code” software exercise may prompt students to engage with AI and ML when these concepts were previously inaccessible to them. Our future work will aim to improve and refine our data collection methods to advance the validity and reliability of our results. These results will be used in conjunction with careful attention and consideration to the course intervention, so that students do not simply see ML tools as a ‘black box’. This remains a significant challenge to the approach described in this paper.

Acknowledgments

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Appendices

Appendix 1

Table 3: Material formulations and 3D printing processing parameters used in the creation of a complete dataset from popular off-the-shelf 3D printing filaments.

Polymer	Fiber Type	Fiber v_f (%)	Bulk/Infill Print Speed (mm/s)	Layer height (mm)	Nozzle temp. (°C)	Bed temp. (°C)
ABS	None	0	90, 105, 120	0.1, 0.2, 0.3	210, 230, 250	100
ABS	CF	10, 20	90, 105, 120	0.1, 0.2, 0.3	220, 240, 260	110
ABS	GF	10, 20	90, 105, 120	0.1, 0.2, 0.3	220, 240, 260	105
ABS	Aramid	10, 20	90, 105, 120	0.1, 0.2, 0.3	240, 260, 280	100
Nylon	None	N/A	90, 105, 120	0.1, 0.2, 0.3	245, 265, 285	65
Nylon	CF	10, 20	90, 105, 120	0.1, 0.2, 0.3	235, 255, 275	95
Nylon	GF	10, 20	90, 105, 120	0.1, 0.2, 0.3	250, 270, 290	65
Nylon	Aramid	10, 20	90, 105, 120	0.1, 0.2, 0.3	235, 255, 275	70
PLA	None	0	90, 105, 120	0.1, 0.2, 0.3	180, 200, 220	60
PLA	CF	10, 20	90, 105, 120	0.1, 0.2, 0.3	190, 210, 230	60
PLA	GF	10, 20	90, 105, 120	0.1, 0.2, 0.3	180, 200, 220	40
PP	None	0	90, 105, 120	0.1, 0.2, 0.3	190, 210, 230	90
PP	CF	10, 20	90, 105, 120	0.1, 0.2, 0.3	215, 235, 255	60
PP	GF	10, 20	90, 105, 120	0.1, 0.2, 0.3	235, 255, 275	90
ASA	None	0	90, 105, 120	0.1, 0.2, 0.3	225, 245, 265	100
ASA	CF	10, 20	90, 105, 120	0.1, 0.2, 0.3	225, 245, 265	100
ASA	GF	10, 20	90, 105, 120	0.1, 0.2, 0.3	240, 260, 280	105
ASA	Aramid	10, 20	90, 105, 120	0.1, 0.2, 0.3	235, 255, 275	90
PETG	None	0	90, 105, 120	0.1, 0.2, 0.3	225, 245, 265	75
PETG	CF	10, 20	90, 105, 120	0.1, 0.2, 0.3	225, 245, 265	80
PETG	GF	10, 20	90, 105, 120	0.1, 0.2, 0.3	210, 230, 250	85
PETG	Aramid	10, 20	90, 105, 120	0.1, 0.2, 0.3	200, 220, 240	90
PC	None	0	40, 55, 70	0.1, 0.2, 0.3	275, 295, 315	115
PC	CF	10, 20	40, 55, 70	0.1, 0.2, 0.3	275, 295, 315	115
PC	GF	10, 20	40, 55, 70	0.1, 0.2, 0.3	285, 305, 325	90

Appendix 2

Table 4: 3D printing process parameters kept constant during the creation of the dataset.

Control Variable	**Value**
Raste Angle (°)	± 45
Build Orientation	XY
Infill Geometry	Rectilinear XY ± 45°
Infill Density (%)	100
Contour/Wall/Perimeter/(Vertical Shell) Count	2
Top Solid Layer (Horizontal Shell) Count	4
Bottom Solid Layer (Horizontal Shell) Count	4
Top/Bottom Solid Layer (Horizontal Shell) Pattern	Monotonic
Support	N/A
Filament Diameter (mm)	1.75
Nozzle Diameter (mm)	0.4

Appendix 3

Table 5: Summer undergraduate research student reflections.

Reflection topic	**Student 1**	**Student 2**
Reflect on your understanding of machine learning and how it has changed (if at all) through your experience on the project.	"One of the most important lessons I learned was the importance of proper exploratory data analysis (EDA) and how obtaining, formatting, and cleaning a dataset is critical to successfully train a ML model." "I have thoroughly familiarized myself with the essential uses, concepts, and steps to successfully apply AI and ML tools in my field."	"Coming from a materials engineering background, I had to learn concepts that someone of a computer science background may have had more familiarity with." "Learning about such a topic through research is no substitute for working directly with a platform that incorporates machine learning."
Reflect on your understanding of how machine learning could be applied to materials engineering problems.	"Anywhere an engineer or scientist has to interpret an aspect of materials to make educated decisions, ML tools can most likely achieve similar results." "Materials informatics is still in its infancy. Many new approaches are currently being researched and should yield intriguing advancements in the field."	"Good datasets will enable machine learning models to predict a plethora of outcomes. More specifically, machine learning models can come in handy when trying to develop multidimensional Ashby diagrams past the comparison between just two material properties."
In what ways do you think machine learning can be used to help solve real-world engineering problems?	"All fields of engineering also benefit from the increased abundance of ML, and those educated in how to apply it can solve a wide range of problems." "A comparison I like to go back to when explaining the usefulness of ML in real-world problems is the advent of Microsoft Excel."	"Machine learning can be used to help solve real-world engineering problems, especially when it comes to optimization. Being able to identify the best and/or worse case scenarios based off numerous factors is becoming something that is more and more difficult in engineering."
Do you think you will need to use machine learning tools at some point in your career? Why/why not.	"I definitely know that I will need to use ML tools and approaches in my future career(s)." "I see it as critical to my success to try to employ such problem-solving approaches to better understand problems at a deeper level and solve them in less obvious ways."	"Yes, I believe I will need to use machine learning tools at many points in my career." "I believe machine learning will eventually work its way into many sectors and industries."