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Analysis of Online Robotics Challenge Submissions - Fundamental

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Introduction

Robotics competitions that bring students together to solve engineering challenges and engage in robot battles have grown in popularity over the last 20 years [1]. With the increase in available educational robotics technologies (such as LEGO robotics, VEX Robotics, micro:bit, and other tools) robotics competitions have become ubiquitous in most school communities around the world [2].

These competitions have been shown to have positive learning outcomes for those who participate [3,4]. Specifically, research into robotics competitions has shown that they positively impact the development of: (1) problem solving skills, (2) self efficacy, (3) computational thinking, (4) creativity, (4) collaboration, and (5) motivation [1]. Additionally, online and in person robotics challenges encourage students to think for themselves and come up with their own ideas in the absence of the step-by-step instructions often provided in classroom settings. Above all else, the literature indicates that robotics competitions provide students with exposure to STEM fields and help increase their likelihood of pursuing a career in STEM [5,6].

The widespread success of many in-person educational robotics competitions combined with the increasing capabilities of the digital world has led to the existence of several asynchronous online robotics competitions [7]. These competitions provide a challenge prompt, deadlines, and criteria by which each submission will be judged. Participants work on the challenge in teams or as individuals and then electronically submit photos, videos, and other documentation of their solution. Examples of such competitions include Hour of Code, CoderZ League, and Zero Robotics [8-10]. As a result of the COVID-19 Pandemic, now more than ever, asynchronous online robotics challenges are engaging a high number of students. Additionally, an online format eliminates geographic and financial barriers often present with in-person robotics competitions.

While online robotics competitions have surged in popularity, they are distinctly different from in-person competitions. In-person competitions bring students together from different schools, states, and even countries. The camaraderie and collaborative aspects of many of these competitions are largely missing from online competitions. Another key difference between in-person and online robotics competitions is the ability to capture and study student learning. In-person robotics competitions allow researchers to collect data, observe students in action, and conduct conventional educational research methods. Online robotics competitions often do not afford this same type of analysis.

Motivation

While the benefits of robotics competitions are well documented and largely undisputed, research into online educational robotics competitions, where students solve a problem asynchronously and submit their robotic solution online, is sparse. We often assume that participants in these online challenges reap many of the benefits of in-person robotics competitions, but there is little research done to confirm this. Rarely are the submissions to these online robotics competitions analyzed in an attempt to try and really understand more about what students are learning. Our main goal in this project was to see what we could understand about student creativity and learning from analyzing online submissions. Typically researchers examine the entire journey of students as they complete a robotics challenge, but we wanted to see how much we could surmise in a situation where we were not able to capture these journeys. Our hope is that this analysis will inform future strategies for understanding student learning when full journeys can't be captured, as well as build a lens that can inform the development of online robotics challenge prompts and supports.

Study Context

Dr. E's Challenges is run by Professor Ethan Danahy from the Center for Engineering Education and Outreach at Tufts University [11]. Dr. E's Challenges provide community members with an opportunity to design, build, and share creative solutions to challenges from anywhere in the world. This online database has a variety of LEGO WeDo and LEGO MINDSTORMS Challenges for students to create imaginative solutions to open-ended problems. Each challenge provides a prompt, a goal, rules, and pictures of example solution ideas. Figure 1 below shows an example of a Dr. E's challenge prompt.

Creepy Crawly

Goal: Make a WeDo creepy crawly—a worm, a bug, a spider, or any creepy-crawly creature.

Start date: March 1, 2019
Due date: March 31, 2019

Rules: You may use only the sensors and motors from the WeDo 2.0 kit, the original WeDo kit, or the LEGO BOOST kit. However, you are welcome to use multiple WeDo kits, BOOST kits, additional LEGO pieces, and non-LEGO materials.

Figure 1: Example Dr. E's Challenge Prompt

Students are asked to submit documentation of their final robot, including pictures, videos, and a written description. There are 48 WeDo Challenges and 40 MINDSTORMS Challenges. Community members submitted nearly 1000 solutions for 88 challenges from 57 countries between 2014 and 2019. We chose to analyze Dr. E's Challenges because of the huge existing database of robotics challenges, the diverse audience of community members, and the original, open-ended LEGO engineering challenges. Figure 2 below shows an example student submission to a Dr. E's WeDo challenge prompt.

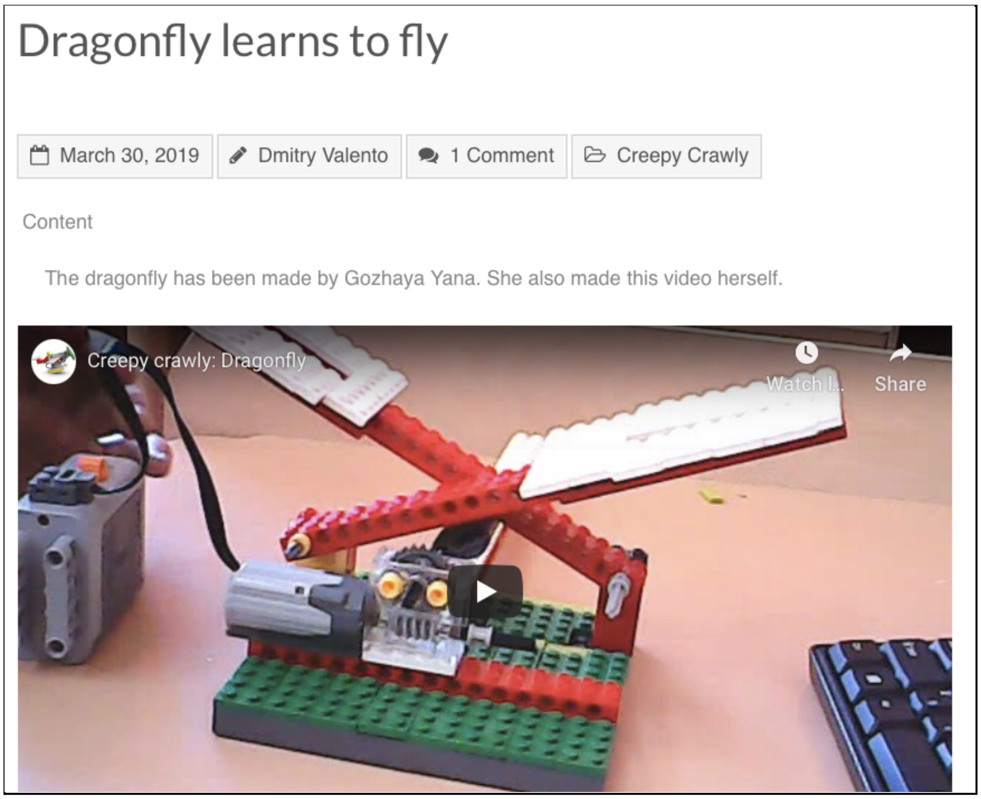


Figure 2: Example Student Submission to Dr. E's Challenge

Data Analysis and Methodology

Our goal in this study was to analyze student learning by looking at the final artifacts that students submitted to each Dr. E's challenge. Artifact analysis as a tool for measuring student learning is emerging as a new alternate method of educational assessment [12]. Most often, student work (or portfolios) are analyzed by an instructor and the quality of the student work is then combined with exam scores to assign students a final grade [13]. In our research, artifact was the sole method through which we sought to understand the kind of learning in which students were engaged when solving Dr. E's challenges.

To analyze the student submissions, we created a coding scheme to classify several categories of student learning and creativity for different metrics. For each submission, we assigned a numerical value for each of the different metrics and provided qualitative descriptions for the robots that students built. These metrics included complexity of code, complexity of build, variance from instructions/examples, simplicity of solution, stability/reliability/functionality, pride (based on quality of documentation), and materials usage. The qualitative descriptions were to describe the motion of each robot, what triggered the motion, the overall build, and anything particularly notable about the robot.

Quantitative Data

We used an open coding grounded theory strategy for analyzing all of the Dr. E's challenge submissions [14]. This allowed us to break down each submission into several key components and then further categorize those components based on a variety of factors to identify meaningful trends [15]. Table 1 below details the coding scheme that we used. Each individual submission in the data set was then collaboratively coded by the two researchers who developed this codebook.

For each submission, we rated the final robot on 7 categories including complexity of code, complexity of build, variance from instructions/examples, simplicity of solution, stability/reliability/functionality, pride (based on quality of documentation), and materials usage. Each robot was rated 0–3 for each category based on specified criteria for each numerical value. A rating of 0 indicated that proper documentation was missing in order to accurately assess the robot's performance in that category. A rating of 1 indicated that the robot performed low in that category. A rating of 2 indicated that the robot performed well in that category. A rating of 3 indicated that the robot performed particularly well and went above and beyond in comparison to other submissions for the same challenge.

Table 1. Quantitative Codes for Analyzing Submissions

Metric	0	1	2	3
Complexity of Code	No code submitted or could not determine based on submission	Code is single thread, no subroutines, no comments, limited coding structures	Code contained some: while/for/if loops, parallel threads, subroutines, variables, arrays, brick-to-brick communication, and is well-documented	Code was complex and had a lot of: while/for/if loops, parallel threads, subroutines, variables, arrays, brick-to-brick communication, and was well-documented
Complexity of Build	No build submitted or could not determine based	Basic construction with simple build techniques	Few iterations to final product, mix of build techniques	Many iterations to final product, innovative use of pieces

	on submission			
Variance from examples	Could not determine from submission	Submission is the same as example	Solution is based on example/instructions but has some differences	Solution is significantly different from any examples given
Simplicity of Solution	Could not determine from submission	Solution is very basic and contains minimal pieces	Solution contains several pieces but has a singular function. Uses a motor or sensor but not both	Solution uses lots of LEGO pieces, motors, and sensors and appears to be a complicated way of solving the challenge
Functionality	Could not determine from submission	Submission doesn't appear functional	Submission works in video but doesn't seem like it would work repeatedly or falls apart after one test	Appears functional and is shown working repeatedly
Quality of documentation	No documentation submitted	Minimal documentation/lackluster photos	Some photos/videos but no text explanations or video narrations	Lots of carefully staged photos, enthusiastic video explanations and write-ups
Materials usage	Could not determine from submission	Used LEGO robotics kit only	Used LEGO robotics kit and other LEGO parts	Used LEGO and non-LEGO parts

We also attempted to quantify the impact of providing examples on the student submissions for all of Dr. E's challenges. For each challenge that included example ideas, we computed what percentage of submissions were a direct replica of the example(s) given in contrast to student inventions.

Qualitative Data

For each submission, we described the overall physical structure of the robot, the way the robot moved, and what triggered the motion of the robot. The robot description included what the robot looked like or resembled, what pieces were used, how the pieces were connected, the relative size of the robot, and anything else that stood out to the researchers such as differing significantly from other submissions for the same challenge or a unique use of the materials. The motion description of the robot, including how well the robot physically functioned and how smooth the motion and gait of the robot was. For different challenges, robots utilized different types of motion such as rolling, driving, walking, shuffling, etc. Some robots moved smoothly while others had mechanisms that caused more choppy or uneven motion. Additionally, uneven motion in the robots was usually an indication that the robot was not fully functional. The trigger description was used to categorize how a robot's motion was initiated.

We also documented the written descriptions that some students provided of their robot. For example, the Waiterbot submission from the MINDSTORMS Cycle 1 Kitchen Helper challenge described the robot as "Built using EV3 brick, a color sensor and a touch sensor to carry snacks from kitchen to living room or any other place really as long as there is a black line for it to follow. Programmed to move both wheels with one moving forward and another moving slightly backward. When it detects black, it steers right and when it detects other color in comparison, it moves left so it always stays on line."

Results

After quantitatively and qualitatively analyzing all of the nearly 1,000 submissions to Dr. E's challenges, we looked for meaningful trends in the data. These various noteworthy relationships are described below.

Notable Quantitative Trends

Our quantitative analysis brought forth a few notable trends and highlighted areas where there was simply not enough information in the submissions to discern whether a trend was present. First, we noticed that when students used non-LEGO materials in their solution, they had a higher quality of documentation. Students had a tendency to take more pictures and submit longer video explanations when their robot incorporated external materials and decorations. Similarly, variance from examples and quality of documentation were also highly correlated, indicating that when students feel like they have come up with something new and original they are more willing to document. The correlation factors between these metrics are documented in Table 2 below.

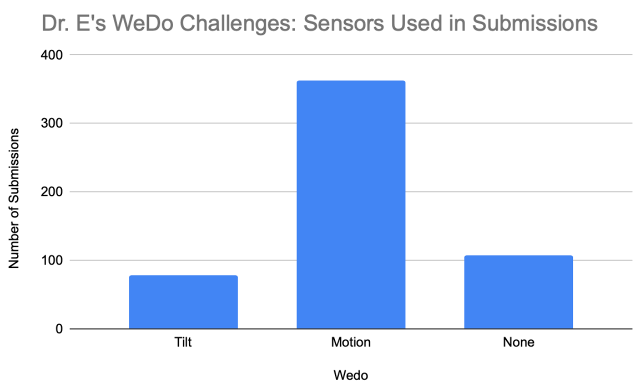
Table 2: Notable Correlation Coefficients between Quantitative Metrics

Quantitative Metrics	**Correlation Coefficient**	
	WeDo	*EV3*
Materials Usage and Quality of Documentation	0.78	0.70
Materials Usage and Variance from Examples	0.65	0.73

Lastly, we noticed a correlation between the functionality metric and the quality of documentation metric. This relationship was not present when analyzing the dataset as a whole, but was high within certain challenges. We also noticed an absence of trends related to the complexity of students' code. This was mostly because very few students included pictures of their code in their final submission; therefore we have no way of knowing what the code written by most students looked like.

Notable Qualitative Trends

We noticed two interesting trends as a result of our qualitative analysis. The first was focused on the types of sensors/triggers students used to activate their robots. Most commonly, students chose to use the motion sensor to trigger their robot to move, where the student would wave their hand in front of the motion sensor to activate the robot. Students less commonly chose the tilt/gyro sensor, where they would hold the sensor and move it to trigger their robot. The least common type of trigger was pressing a key on the computer or a button on the robot to start the code and activate the robot. For the MINDSTORMS challenges, 137 submissions used the ultrasonic sensor and 95 submissions used the touch sensor. For the WeDo challenges, 241 submissions used the motion sensor and 38 submissions used the tilt/gyro sensor. These data are shown in Figure 3 below.



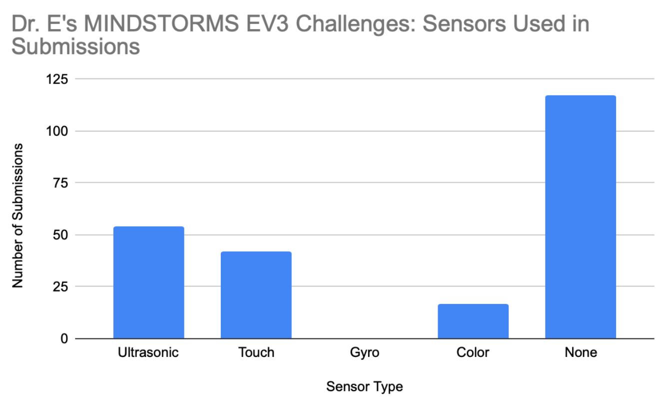


Figure 3a(Left): WeDo Sensors Used in Submission, Figure 3b (Right): MINDSTORMS EV3 Sensors Used in Submissions

Another notable trend was the impact of provided example ideas on student submissions. Example ideas and pictures were provided for the WeDo and MINDSTORMS EV3 challenges. For example, the Bakery Bot challenge in Cycle 10 of the WeDo challenges asks students to "Create a device to aid the busy bakers—a cake froster, a bread kneader, a dough mixer, a cookie cutter, or some other tool to help make sweet treats." These examples are meant to provide some guidance to students who may be struggling to get started or come up with their own original ideas to tackle the challenge. Some challenges, such as the Cycle 3 WeDo Challenge, were more specific and asked students to build a burglar alarm; therefore there was only one example to follow, and these challenges were not included in the example tracking analysis.

We found that over 40% of submissions on average for that challenge were a replica of one of the examples provided. This percentage indicates that students had a significant tendency to follow one of the given examples instead of coming up with their own unique solution or attempting to generate original ideas for the challenge. There were, however, notable outliers. For example, with the Cycle 8 WeDo Robochef challenge, no submissions followed an example (0/7). The given examples included slicing bread, stirring a pot, and making a sandwich or ice cream sundae. Instead, students came up with ideas such as a potato masher, dish dryer, meat grinder, dough mixer, folding table, automatic mixer, and plate dryer. Some of these solutions are shown in Figure 4 below. While this may be attributable to the small amount of submissions, it may also be related to the creative and open nature of this particular challenge.

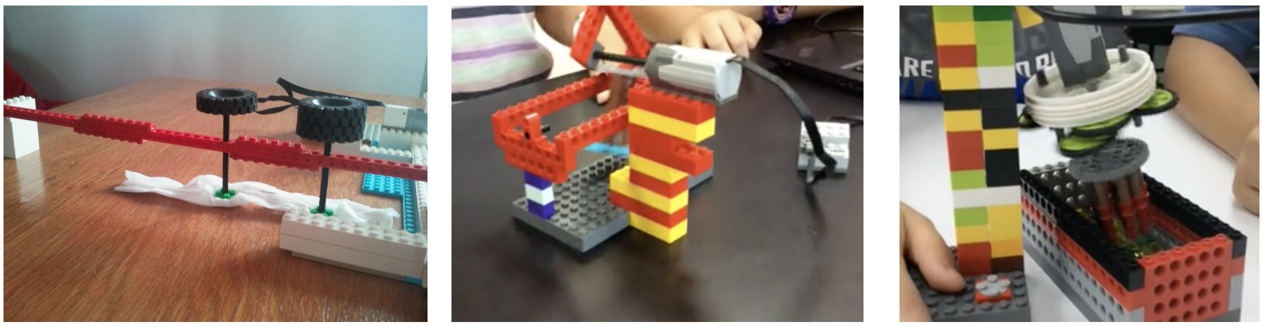


Figure 4a (left): Dish Dryer robot, Figure 4b (middle): Potato Masher, Figure 4c (right): Dough Mixer

In addition, in the Cycle 10 Space Exploration WeDo challenge, all of the submissions followed one of the examples given (7/7). In Figure 5 below, you can see how four of the submissions were of a "space rover," all of which featured a wheeled base with a front-mounted distance sensor.

Figure 5: Four submitted solutions to the "Space Exploration" Challenge

Discussion

The data analysis across the WeDo and MINDSTORMS challenges showed that children have a tendency to follow examples more closely when they are provided, rather than trying to come up with a unique and original solution on their own. By giving text examples, some students may have internalized these examples as being "correct" answers and therefore defaulted to building them. This can be counterproductive in the classroom, as it does not allow students to think for themselves since they are being influenced by what they perceive to be the right robot to solve the challenge. This idea is more formally referred to in the learning sciences as functional fixedness, which is the ”tendency to think about familiar objects in familiar ways that may prevent the objects from being used in novel ways” [16]. We hypothesize that if students are asked to complete robotics challenges without being given any example ideas, then they will come up with more unique, creative, and original solutions on their own and gain a deeper level of understanding and learning as a result. Furthermore, this would allow students to approach the problem with a completely open mind about how to solve it. However, removing examples could also make it more difficult for students to get started and come up with ideas which would hinder participation.

Another clear trend was the relationship between quality of documentation and materials usage. This indicates to us that when students built a robot that was unique and contained specific components that they selected, it made them more eager and excited to share it with others and made them more proud of what they made. Many students used external materials such as paper and pipe cleaners to add features and details to their robot. For example, some students used external materials to add faces or diorama backgrounds to their robots to elevate them. Students who went a step further and made their robot more aesthetic or decorated had a tendency to take more pictures and videos to document their submission. In addition, some students seemed to incorporate external materials (like tape, string, or rubber bands) after they repeatedly struggled to solve the challenge with just the LEGO kit. Thus, some submissions that demonstrated exceptions to this trend in that the robots scored high for materials usage but lower for quality of documentation can be explained by students using external materials in place of certain pieces in the LEGO kit rather than using external materials to supplement the LEGO kit. There was also a strong correlation between variance from given examples and the quality of student documentation. This again indicates that when students feel that their ideas are unique they are more willing and excited to share them and thus take more pictures and videos to submit. Lastly, the correlation between the functionality metric and the quality of documentation may indicate that when students produced a robot that didn’t work they were less inclined to document, or perhaps to submit anything at all, despite the fact that they may have learned something in the process of attempting the challenge.

Limitations

Our methodology had some inherent shortcomings due to a variety of uncontrollable factors and variables in analyzing the submissions. The analysis was limited to the documentation provided by each community member. Some users did not submit pictures, videos, or descriptions and other users did not document the code used for the robot. With these elements missing, the submission was more likely to score lower in most areas since there was no way of knowing how the robot performed without documentation. Furthermore, being limited to the information submitted, there was no way to account for the many variables implicit in the projects. For example, most students worked alone but many worked in pairs or larger groups. In some submissions where the students worked in pairs, a common recurrence was for one student to do the coding and the other to build the robot. Additionally, while the majority of students built their robots at home, some students completed their projects as part of a class assignment in school or for a robotics program with more instruction and guidance. Outside assistance from parents, teachers, or older siblings was also not accounted for, nor was the previous experience level of students. We have no idea of knowing what students learned as a direct result of completing a Dr. E's challenge or what knowledge students already had as a result of other classes or robotics competitions.

Throughout much of our analysis, a common theme was how much we were unable to infer or analyze about the student experience due to a lack of information provided by the students. The Dr. E's challenges website contained a "Drawing Board" section where students could post flops (failed designs) and work in progress robots. However, students rarely utilized these spaces to document their process, and only two flops and ten works in progress were ever posted. In their submissions, students did not include documentation of their iterative process, screenshots of their code, or any kind of explanation of their background experience with robotics, who they worked with, for how long, and with how much help. This lack of available information on the student process makes it difficult to understand and analyze some aspects of student learning. Being able to interview students or have them answer specific questions about their build process and design decisions would have allowed us to group submissions and infer more about patterns and trends that arose. Similarly, if information was provided about students' background this would allow us to group submissions and analyze them based on common factors. Additionally, when looking at the sensors used to trigger students robots, there was an overwhelming use of the motion sensor in the WeDo challenges, while in the MINDSTORMS EV3 challenges most submissions did not use a sensor, and not one submission leveraged the gyro sensor (which comes in each kit). These aspects of the data remain somewhat of a mystery, and what we were unable to discern from the data present in the Dr. E's challenges data set opens up ideas for additional information that robotics competitions may want to ask for to better facilitate student learning and be able to judge students based not only on their final product but also on their overall build and design process.

Implications and Future Work

Our findings have a few key implications. First, the insights gained through our example tracking reinforce the notion that students tend to come up with more creative and original solutions when they have more flexibility to think for themselves rather than relying on instructions and being influenced by examples. In the future, a comparative analysis of the robots students build for LEGO engineering challenges where one group of students is asked to complete the challenge and given examples while the other group of students is asked to complete the same challenge but given no examples would be particularly insightful and could provide greater understanding as to how increased guidance and instruction hinders student creativity and learning. We hope to investigate and develop more ways to help students get started without implying that there is a correct solution to the problem.

An ideal online robotics challenge would account for outside factors and use this information to inform how the robots that students produce are analyzed. These outside factors include age; type of collaboration; help from parents, teachers, or instructors; resources; time; and previous robotics knowledge/experience. Students would also have clear requirements for their submission, such as submitting pictures from different angles, copies of their code, a video of the robot in action, and a video explanation. Requiring students to submit all of these materials would make the documentation consistent for each robot and allow for more complete comparisons and analysis. Additionally, students would be asked to fill out a questionnaire that includes questions about background information such as the outside factors and a reflection about what they learned from building their robot. Students would also be asked to fill out the rubric with the coding metrics and score their robot in each of the areas. This would allow for the analysis of the robots to potentially be broken down into different categories based on the information provided by students. Correlation factors between the outside factors and coding metrics would be analyzed and compared. In addition, being able to compare how students scored themselves to how we scored the students for the coding metrics would allow us to see how well a student's perception of their learning and understanding compared to our artifact analysis of their robot. However, adding more requirements for submission may raise barriers to entry and ultimately lead to fewer submissions.

Moving forward, we hope to apply the insights gained as a result of the example tracking and artifact analysis of the Dr. E's MINDSTORMS and WeDo challenges to improve future engineering robotics competitions. The implications of our findings are particularly relevant to enhancing student learning through online educational robotics competitions given how the world is adapting to online learning amidst the coronavirus pandemic. Virtual engineering design challenges provide the opportunity for students to continue engaging in hands-on learning throughout online school. However, changing online robotics competitions to feature the student process as well as the end product may allow for a better window into what they are actually learning, and privilege engineering practices like iteration.

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