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Designing and Evaluating Instructor Training for an Online Machine Learning Course

Jule Schatz, University of Illinois at Urbana - Champaign
Max Fowler, University of Illinois at Urbana - Champaign

Max Fowler is a Teaching Assistant Professor in the Siebel School of Computing and Data Science at the University of Illinois Urbana-Champaign. Much of Max's research is in the space of skills and assessment: specifically identifying the core competencies of programming (and, increasingly, skills for working with generative AI) while developing strategies for fair, secure assessment-at-scale. His work in this space includes leveraging GenAI for autograding and feedback provision, intersecting with "LLM-as-judge" methodologies.

Melissa Jane Ference, Cornelll University
Dominic Andrew Diaz, Cornell University

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Abstract

This Evidence-Based Practice paper describes the design, implementation, and evaluation of an instructor training program developed for the Break Through Tech AI initiative, a national effort to broaden access to artificial intelligence (AI) education for undergraduates. As AI reshapes industry and education, the ability of instructors to create inclusive, rigorous, and engaging learning environments has become critical. To support this goal, the program developed a scalable instructor training model for its online Machine Learning Foundations course, which serves as the entry point to a year-long AI experience.

The training combines asynchronous modules with interactive, scenario-based synchronous sessions emphasizing inclusive teaching strategies, engagement in mixed-ability classrooms, and maintaining academic rigor in a supportive virtual environment. We share outcomes from pre- and post-training self-efficacy data that demonstrate gains in instructor confidence, particularly in preparing engaging online labs and using student data to support learning.

We also identify challenges, such as providing sufficient opportunities to practice responding to disengaged students, and discuss planned iterations to address them. Lessons from this experience offer practical recommendations for others developing scalable instructor training in technical and online contexts.

Introduction

AI (artificial intelligence) is becoming increasingly impactful in our day-to-day lives. Continued excellence and ethics in AI requires we empower a wide range of students to grow their education and take part in AI leadership. However, many computing students face barriers to entering the AI workforce and becoming leaders in this space. It is currently a challenge for many US students, especially those from non R1-universities, to get the experience required to land top internships in the AI field. These internships often pave the way to industry jobs and leadership positions. The Break Through Tech AI Program is a 12-month program aimed at expanding access to career pathways for undergraduate students pursuing tech careers by equipping aspiring technologists with the technical skills, professional readiness support, and real-world project experiences to break into tech roles.

The Break Through Tech AI Program features three components, the first of which is an intensive summer machine learning course. This online course, ML Foundations, focuses on the theoretical, practical, and ethical components of machine learning. It consists of both synchronous and asynchronous online components. Afterwards, students proceed to portfolio development work where they take on a real-world machine learning challenge project to develop professional portfolios with guidance from industry and academic advisors, and professional mentorship designed to inspire and support them. The program has seen significant success, with nearly 80% of students getting a tech related paid internship upon completion. Given the success and potential impact, Break Through Tech has made strides to expand its AI Program to reach more students. One key step is recruiting more instructors to expand access to the ML Foundations course. As the program increases the number of instructors it becomes increasingly important to train and prepare instructors for their unique role in teaching the students of the program.

This paper describes a new training program developed for instructors of the online ML Foundations course. The main goals of the training were to help give instructors the confidence and skills to build a culture of support, an engaged classroom, and a culture of rigor. Because the program runs online and serves students with mixed backgrounds and abilities, the training focused on strategies expressly designed for this setting. Our goal with this paper is to share our training approach and lessons learned to inform the creation of other future training programs. Next, we present some background on the Break Through Tech AI Program and its students, describe previous work in this area, detail the training program we built, relay results from the training, and provide our reflections on what went well and what can be improved.

0.1 Break Through Tech AI Program

Break Through Tech is an Initiative of Cornell Tech that is changing the path to power in tech by propelling undergraduate talent that is all too often underestimated and overlooked into fields that are defining the future. Founded in 2016 by Dr. Judith Spitz, former CIO of Verizon, Break Through Tech empowers, trains, and connects undergraduate students from different lived experiences to professional opportunities in tech across sectors, including AI and Machine Learning (ML).

The Break Through Tech AI Program is a 12-month long program which begins with a 9-week summer course called ML Foundations. The ML Foundations course features asynchronous online learning modules complemented by weekly 3-hour synchronous labs taught by PhD students or faculty in computing fields (instructors). The course focuses on teaching practical machine learning skills and industry tools that will prepare students for technical careers as AI/ML engineers and data scientists, including the development of an industry-ready project portfolio. An ML Foundations course instructor's main role is to facilitate a 3-hour lab, grade assignments, and answer questions during the week. Instructors are not expected to create labs or material, instead they are expected to adapt and adjust given material for their lab and provide support to the students on each week's asynchronous material. The instructors are recruited from various US universities and were selected for their ML knowledge, teaching skills, and inclusive mindset.

The ML Foundations course is currently being expanded using an instructional hub model where different institutions of higher education (IHEs) lead one or more sections of the ML Foundations course. Note that while a single university hosts a section of the course the students in the section come from a large variety of US colleges and universities (200+). The hub model was first piloted in 2023 with Hofstra University. In 2024, the program expanded to 8 sections (480 students) hosted by 4 hubs. Now, in 2025, there are 15 sections (˜900 students) across 10+ instructional hubs. In the next three years the plan is to expand to 25 sections (˜1,500 students) across up to 25 instructional hubs. This means the training for the ML Foundations instructors will expand from training 15 instructors from 10+ universities this year to potentially 25 or more in the next few years. This expansion and potential impact to a large population of students motivated us to focus on the training provided to the ML Foundations instructors. As the number of institutions expands it will become increasingly important to provide a strong training foundation to all instructors to maintain the high level of success of the program.

1 Related Work

1.1 Large CS Outreach Programs

The Break Through Tech AI Program is one of many large outreach programs that have seen success over the years. A popular form of outreach are programs using robotics, implemented in ways from *LEGO*® kits to more advanced programming tools[1,2,3]. Similarly, cybersecurity outreach has a notable footprint in the space of available outreach content[4,5,6,7]. Other programs that teach machine learning and computer science have also included training for facilitators. For example, CSForALL[8,9] and the Farleigh Dickinson University CS Hub[10].

1.2 Programs for Undergraduate Teaching Instruction

While there is a notable body of work on education and professional development programs for K-12 CS instruction[11,12,13,14], much of the literature on training instructors for *undergraduate instruction* focuses on training during graduate student careers (such as with a methods course[15]) or as TAs. We briefly review some of these programs below as similar to our own professional development program.

Mirza et al.[16] provide a systematic review of the state of CS undergraduate TAs up to 2019. The review provides more detail on undergraduate TAs' responsibilities and recruiting than specific training details, although briefly summarizes several models. Most similar to our training model are undergraduate training programs conducted in a workshop style format[17] with a focus on teaching techniques[18,19] and working with different students and course situations[20,21]. Several training programs are more similar to our training program in that they occur yearly or before specific semesters, as opposed to continuously during an academic year[22,20,23]. Our training differs the most from these in that our audience consists of instructors (graduate students and teaching faculty) from many different institutions (10+). This led us to having more activities where participants share their own insights, rather than just us instructing. Our goal was to leverage all the expertise and varying experiences in our group.

Minnes[24] describes the CS TA training at the University of California, San Diego. While their training is weekly, they share in common with our training program the option for synchronous training via zoom. They ultimately found peer engagement and reflection were found to be particularly useful by their TAs and that training can benefit by centering research backed best practices[24]. We incorporated this insight by also centering our training modules around researched backed best practices.

Muzny and Shah[25] detail their TA training curriculum modules and their results after using it at two institutions. Their modules were designed to be synchronous but timing and modality flexible, allowing for everything from a single, hour-long session to a full 1-credit course. In shorter trainings, these modules emphasize, among other topics, the importance of rapport building, dealing with scenarios that are common in student interactions, and considering the experiences of students in the course[25]. Our training incorporated the ideas around being a flexible modality by having asynchronous and virtual synchronous components. However, we strayed by having the synchronous component be 3-hours long instead of 1-hour long. We found that, for our audience (graduate students and teaching faculty), participants preferred large chunks of time to many small chunks. However, our training followed Muzny and Shah[25]'s lead by having a focus on rapport building. We had activities that helped facilitate a rapport between participants and showed them examples of how to create rapport between their students. We also had modules on common student interactions and emphasized compassion around student experiences.

The Break Through Tech training program is similar to the above in that it centers best practices for student engagement and support and not only pedagogical content knowledge. We share the insights and results from our training to share how one well-developed training can impact a wide range of students across multiple sites via the hub model.

2 Training Design

The instructors come in with ML knowledge and basic teaching experience. Our goal with the training was to help further their skills around teaching Break Through Tech students (who come from a large variety of universities and colleges (200+)) and to help them navigate teaching in an online setting. The audience for the training ranged from new PhD students to experienced teaching faculty. To navigate this range of incoming skills, we focused many activities around group discussions and sharing experiences. The goal was to leverage the different expertise and experiences of the instructors, and not just the facilitators. We also used this technique to show instructors how they might adjust the labs they run to accommodate the wide range of students they will see.

The training was designed by a small team which make up a majority of the author list. It was designed to be finished before the instructors begin teaching their ML Foundations course. Once they begin teaching, there are additional supports in place, including a community of practice and peer instruction feedback. The instructor training consists of asynchronous and synchronous online components. The synchronous component took place over two weeks and consisted of four online 3-hour sessions each with a different theme.

1. Building a culture of support
2. Building an engaged classroom
3. Building a culture of rigor

4. Navigating course operations

The themes were selected by the facilitators because of the importance we believe they have to instructor success during the course. Later, we will discuss potential adjustments to the themes based on our experience this year. We will delve into the first three sessions into more detail as we believe they had the largest impact and are more widely applicable. The fourth session, while important, focused on workflows necessary to manage course logistics, grading, and student communications. We do not share more details on this portion in this paper but welcome inquiries.

Each synchronous day was facilitated by 1-2 members of the training design team over video conferencing to the 15 instructors. The training was designed to both explain and demonstrate how to facilitate a 3-hour online session effectively. The training provided instructors with a Reflection and Action Guide to capture ideas from the training and plan out actions they can take to implement these ideas. It was structured around the three main training themes (support, engagement, and rigor). After each day, instructors were asked to reflect on the guide on the "strategies and activities I want to use," "instructor language or tone I want to adopt,", "challenges I anticipate and how I might navigate them," and to list two of their key takeaways from the lesson. Additionally, days 1–3 each had day specific questions on "ways to achieve a supportive classroom,"ways to achieve an engaged classroom," and "ways to achieve a culture of rigor." Days 1 and 3 also had pre-lesson reflections on what instructors may anticipate about their ML Foundations students and what communication style they want to adopt for their class sessions. Our goal was to create a document that instructors could return to during their teaching experience and consult their notes when navigating real classroom scenarios.

2.1 Async Training

Before beginning live training, all training participants completed asynchronous pre-work designed to provide a shared foundation of knowledge about Break Through Tech, its AI Program, the students, the course they are delivering, and Break Through Tech's expectations for course facilitation and support. It was meant to provide the "what"—the knowledge and tools needed—so that they could focus on strategies for effective teaching during live training. Completion of the asynchronous training was measured through a series of summative assessments confirming understanding of the background knowledge so that participants attended synchronous training ready to apply what knowledge they acquired.

2.2 Session 1 – Building a Culture of Support

The learning outcomes for this session included knowing how to create a supportive learning environment, how to foster resilience and student-centered learning, and how to elevate fellow voices and build community. After an icebreaker and introduction to the training, these learning outcomes were facilitated through three sections: mindset, strategy, and application. These sections were designed to move us from foundational ideas (mindset) to practical teaching techniques (strategy) to real-world scenario practice (application).

The mindset section involved a student panel and related reflections. We recruited five former

Break Through Tech students to answer questions and share their experiences from their ML Foundations course. They answered questions like “Can you share a specific moment when you felt particularly included and supported in the classroom?” and “Can you share an example of how instructor feedback helped adjust your learning approach?”. The idea was to motivate instructors by having them hear from students and learn what impact their actions can have. After the panel, when the students left, the instructors were encouraged to reflect on if their preconceptions of students were challenged during the panel. This section was designed to motivate and address the learning outcomes for the day while getting the instructors in the mindset for the rest of training.

The strategy section involved the facilitator demonstrating a portion of the ML Foundations lab that the instructors would later run in their own course. The facilitator showed how to encourage a growth mindset, encourage students to build off of each other’s answers, and use “wait to respond” activities to encourage more participation. Another focus of the demo was to demonstrate multiple avenues for fellow participation during lab, encouraging a wider range of fellows to interact with the material. This section concluded with a breakout room reflection session for instructors to collaboratively synthesize what parts of the demo they want to use in their own course. This section was designed to show how an instructor can use different strategies to create a supportive classroom where fellows feel comfortable and excited to engage with the content.

The application section consisted of the instructors going into breakout rooms and discussing potential scenarios they might face in their lab. The scenarios covered topics including elevating voices and building community, fostering resilience, and creating an inclusive environment. This section aimed to build community among instructors and help them critically think about issues that could come up while they are teaching around building a culture of support.

2.3 Session 2 – Building an Engaged Classroom

The learning outcomes for this day included knowing how to utilize virtual tools to encourage engagement, how to use engagement tools to shift participation from passive to active learning, and how to recognize that facilitation style has a significant impact on fellow engagement. This day was structured to demonstrate an entire lab that instructors would deliver in their own course. The goal was to provide instructors context for their upcoming labs rather than a rigid blueprint.

The demo lab was broken into three sections (similar to the actual lab): the intro, the concept review, and the lab work time. For each of these sections, there was an introduction/motivation, the demo (with the facilitator pretending to be the instructor and the instructors pretending to be students), open ended reflection, behind the curtain information, and small group discussions.

The introduction/motivation setup each lab section for the instructor so they understood some context before the facilitator started the demo. The demo was run by a facilitator that taught the ML Foundations course the previous summer. After the demo, the instructors were asked to reflect on what they saw, both negatives and positives. The facilitator guided them to notice specific teaching strategies and techniques used, such as incorporating real world examples or using zoom polls to gauge understanding. Next, the facilitator shared some behind the curtain information on how she prepared, facilitated, and reflected while adapting that portion of the lab. To finish off the section, instructors were put into small breakout rooms, and asked to reflect on what they observed guided by structured questions.

2.4 Session 3 – Building a Culture of Rigor

The learning outcomes for this day included learning how to balance support and rigor, how to promote critical thinking and problem solving, and how to differentiate instruction to meet all learners' needs. This day was specifically added to address feedback that advanced students sometimes felt unchallenged in previous iterations of the ML Foundations course. We wanted to show instructors how to engage all students while remaining encouraging and supportive. Like the first day, after an icebreaker, these learning outcomes were facilitated through three sections: mindset, strategy, and application.

The mindset section revolved around education with Radical Candor[26]. Radical candor revolves around the idea of being supportive while remaining truthful and direct. Instructors worked in teams to create a presentation slide on one of the following related terms: radical candor, ruinous empathy, obnoxious aggression, or manipulative insincerity. Afterwards, each team presented their slide to the group. The goal was to show how to use an interactive activity to teach a concept and to teach the concepts around radical candor.

The strategy section focused on teaching the instructors how to scaffold questions to get to complex topics from simple ones. After an introduction and demo the instructors were asked to scaffold an ML topic in small groups. We had the groups share their questions in a collaborative document and give feedback to other groups. This was both to show them another engagement strategy and to help them learn about scaffolding questions.

The application section was open ended time for the instructors to start working on preparing for their first lab. They were put into breakout rooms and given the lab 1 starting material. They were encouraged to think about everything we had covered in the training so far as well as look at their Reflection and Action Guide to inform how they would facilitate their lab session. This provided lab facilitators with time to synthesize what they learned throughout the first three days of training and begin translating the concepts covered in the training into their own teaching approach.

3 Results and Reflection

To measure the success of the training, an outside evaluator surveyed the participating instructors both before and after the training but before the ML Foundations course started. The outside evaluator used Likert scale[27] self-efficacy questions centered around the goals of the training and the overall mission of Break Through Tech AI.

We focus on instructor self-efficacy as a way to measure where our training impacts instructors' perceived preparedness for ML Foundations instruction. Improved self-efficacy in particular has myriad benefits for teachers, including reduced teacher burnout, the capacity to better motivate students[28], better classroom practice, higher job commitment[29], and better utilization of instructional resources[30]. Gauging self-efficacy provides a useful signal for where instructors

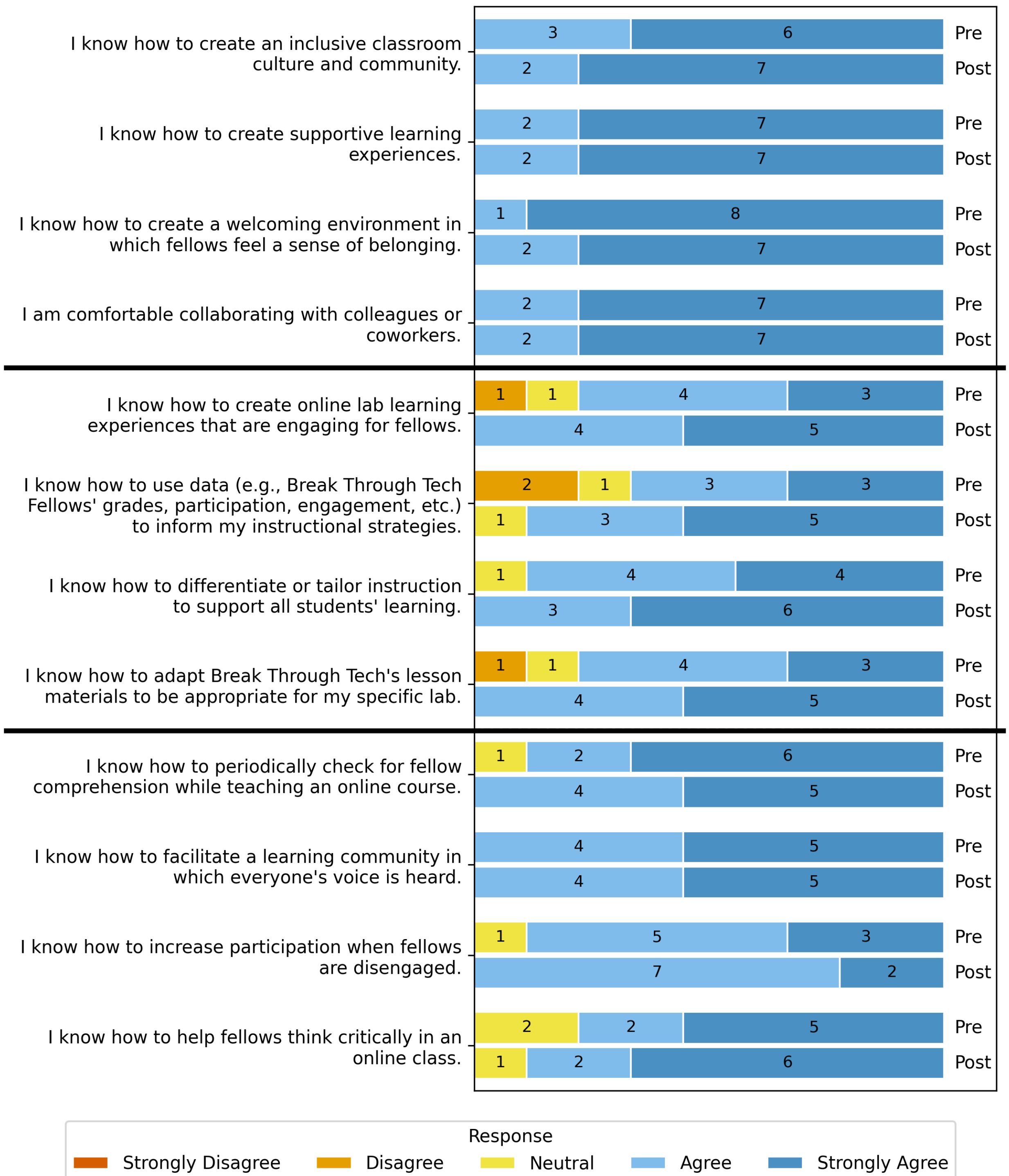

Figure 1: Self-efficacy Likert scale question results from the 9 participants. They are split (by a line) into three groups starting from the top, "already mastered", "clearly positive", and "needs improvement". Each question is presented as a pair of results, the pre-survey (top) and post-survey (bottom).

both feel capable to succeed and are likely to have positive outcomes for their students. Out of 15 instructors there were 9 that filled in both the pre and post survey which we used for evaluating. Additionally, we obtained feedback from students of the ML Foundations course three weeks into the course. Of the 705 students who responded, 65.67% of students responded with ‘strongly agree’ and 31.21% with ‘agree’ when asked if their lab facilitator effectively led and facilitated lab sessions. This positive student feedback suggests that the instructors were prepared to create positive and effective learning experiences.

The training was well received with 100% of the post survey participants (N = 14) indicating they agree with “I am satisfied with the training experience that I received during the Break Through Tech Train the Trainer program.” Additionally, almost all the responses to self-efficacy questions were Agree or Strongly Agree following the training, with only two “Neutral” responses (Figure 1). Based on these measures, the training was a success. Even so, we want to continuously strive towards improving. This will be especially important when continuing to scale to even more instructors. To do this, we viewed the results through an especially critical lens, striving for a large majority of “Strongly Agree”s for every self-efficacy question.

Figure 1 has 12 out of the 14 self-efficacy questions given to participants and the results from the 9 participants who filled out both the pre and post. We removed two questions from the analysis because we did not feel that our training was directly related to these items. The removed questions are: “In general, I feel confident about my ability to learn new things.”, and “I know how to prepare fellows for real machine learning careers.” Neither of these topics were covered explicitly during training. During post analysis, we divided the questions into three groups: already mastered, clearly positive, and needs improvement. Already mastered are the questions where a large majority of participants indicated strongly agree before and after the training. Clearly positive are the questions where we were most satisfied with the improvements shown. Needs improvement are the questions where we wanted to see more improvement than what we got given the goals of the training. Next, we look at each of the groups in more detail.

3.1 Already Mastered

The already mastered questions are ones we identified as instructors having come in with strong self-efficacy and left with similarly strong self-efficacy. The specific four questions and the results are the top four questions in Figure 1 (before the first line). Every one of these questions started and ended with a large majority of “strongly agree”s and had no responses marked as less than “agree”.

When looking at the content of these questions, we saw that the first three revolve around an instructor’s ability to create inclusive, welcoming, and supportive environments in general. The 4th question revolved around collaborating with colleagues. Our instructors were hired in part because they displayed these qualities so it makes sense they indicated high self-efficacy on these. Further, it may be that creating environments that are generally supportive is an easier task than intervening to re-engage specific students (an area we identify for more growth later on). Given the high starting self-efficacy and the lack of change, we cannot evaluate the potential impact of our training on these attributes. However, it will be important to maintain these high levels of reported self-efficacy in future offerings of the training.

3.2 Clearly Positive

The next four questions in Figure 1 are the questions where we were most happy with the improvements. All of the questions in this section had some participants mark “disagree” or “neutral” in the pre survey and saw growth toward stronger self-efficacy after the training. Additionally, the number of “strongly agree”s went up by two for each question in the post surveys versus the pre surveys. It is also worth noting that these four questions had the lowest self-efficacy reported in the pre survey out of all the 12 questions. While there is still room for these areas to improve, the notable increase in instructor self-efficacy makes this a satisfying result for the training.

When looking at the content of these questions, we saw them all relating to skills specific to the ML Foundations Break Through Tech course and students. They included self-efficacy around online teaching, using Break Through Tech student feedback/data to tailor instruction, and personalizing given material. We attribute this success to multiple strategies we implemented. First, we gave instructors actionable tools, such as how to use video conferencing polls to assess student learning, or how to use a virtual collaborative whiteboard to encourage participation in an online setting. Second, a lot of time was spent demoing the actual lab and showing a behind the curtain view of how it was personalized and adjusted. Third, we integrated many opportunities for instructors to reflect and think critically about what they were seeing in the demos. Fourth, we provided instructors time to workshop and tailor their own upcoming lab in small groups. We think that together these helped instructors feel confident that they could create and adapt their lab to support and engage Break Through Tech students.

3.3 Needs Improvement

The last four questions are ones where we did not see the improvement we would have liked to see in self-efficacy. Even though the results in the post survey for these questions are mostly “agree”s or “strongly agree”s we had expected a stronger movement towards “strongly agree” given the content of our training, similar to the level of agreement of the first four questions in Figure 1. We use these four questions to help guide us in future improvements to the training program.

When looking at the content of these questions, we saw them all relating to an instructor being able to adjust and personalize instruction for *individual* students. They included self-efficacy around how to gauge students’ understanding, how to adjust so everyone’s voice is heard in the class, what to do if a student is disengaged, and how to help individual students think more critically about the content. These differ from the already mastered items as, rather than focus on overall environment, they focus on specific mid-instruction course corrections and interventions. We believe this is an area we can better demonstrate and emphasize in our training. However, it may also be the case that instructors may be less inclined to show strong self-efficacy on questions related to individual students versus the group or environment as a whole. Arguably, these are strictly harder tasks than those at a full classroom environment level.

Reflecting back on the training, we do currently include activities aimed at addressing these topics. The training included having instructors work through possible student scenarios, practice creating scaffolded questions, and showing instructors how to create and run engaging activities through demos. This reflection may have been too surface level and did not explicitly provide actionable tools and ideas of what to do in the moment. Additionally, some of these items could have been extended and refined to provide a greater depth of guidance. For example, we could have included more possible scenarios for instructors to work through that covered more realistic and nuanced situations. It may also be that our lab demonstration student role playing was not sufficiently realistic, given instructors were pretending to be students, for the training to produce stronger self-efficacy in this area. The lab demo arguably ran *too* smoothly, making it insufficient for demonstrating how instructors can recover when a lesson does not go to plan.

4 Conclusion and Takeaways

Overall the training was successful with all post survey participants (N = 14) indicating they agree with "I am satisfied with the training experience that I received during the Break Through Tech Train the Trainer program." Additionally, all self-efficacy questions related to topics covered in the training ended with a large majority of "agree"s and "strong agree"s. We were happy to see participants come in and leave with strong self-efficacy around creating inclusive and welcoming environments. The training did particularly well in addressing what the incoming instructors were least confident about, which was how to prepare an engaging online lab and incorporate student data. One weakness we identified in our training, through the self-efficacy questions, was that it lacked practice and instruction around adjusting during the lab to adjust to individual students struggling.

Moving forward, we have multiple ideas for improvements. For example, the pre survey is currently conducted with only a small gap between the survey and the training itself. In the future, it would be ideal to have the pre survey results collected with enough of a gap before the training such that we could reduce the time spent on topics participants already felt confident in and spend more time on skills they needed to improve on, potentially changing the theme of a training. One way to make this more feasible would be to modularize the training so that sections could easily be slotted in or removed last minute depending on participants' pre survey answers. One challenge with this approach would be making sure the training is still cohesive and flows in a way that makes sense to participants.

We also want to improve the training to address the items where we didn't see high improvement in self-efficacy. These were the questions around helping individual students who are struggling or disengaging. One idea is to include better motivated and more realistic scenarios for instructors to work through in small groups. The scenarios should be focused on how to increase engagement and participation during the lab, especially if things don't go as planned. One idea to better motivate the scenarios is to have the students in the student panel introduce them or mention some aspects of them. This would give the situations more credibility when brought up later on. Additionally, we could call in instructors to share experiences of when they faced disengagement or an activity they planned didn't go well. This would help leverage the expertise in the room, build community, and widen the possibilities of scenarios we can come up with. Overall, we plan on spending more time on going through scenarios in the future. We acknowledge that a high level of self-efficacy already may mean growth on these items will be particularly challenging to achieve, but nevertheless find it worthwhile to attempt to iterate on these items.

Another idea is to, during the demos, have other facilitators act like disengaged students and show different strategies to handle those situations. We could develop specific scenarios or scripts that simulate common student scenarios, such as a student who stops participating mid-class, someone expresses frustration with the material, or a participant who dominates discussion time. This would be best if followed by explicit reflection and discussion on what happened. This would show a more realistic view on what might happen during the lab and provide instructors with a toolkit of responses they can use if they encounter similar situations in their own teaching.

We recognize that our Reflection and Action Guide may not have been as effective in helping instructors develop confidence in navigating various classroom scenarios. Despite the guide included dedicated sections for instructors to plan "a supportive classroom", "an engaged classroom", and "a culture of rigor", three of the fours areas where instructors showed limited improvement directly related to these themes: facilitating a community where all voices are heard, increasing participation among disengaged fellows, and promoting critical thinking. While we provided space for this reflection, the guide may need a modified implementation to help lab facilitators turn reflections into actions they can use in their lab section. Iterating on this document is an area of future work, and we would appreciate feedback from the community on how to modify and integrate this document better.

While the training was specific to the Break Through Tech AI Program and its ML Foundations course instructors we think there are multiple takeaways that could apply more generally. For example, creating engaging and helpful online training is possible. It could be aided with pre survey information and modularizing the components for easy adjustments. Additionally, we found that it is helpful, when running a training, to incorporate both tools and information for the specific context while also zooming out and providing general information and skills around teaching and working with students. Our current training implicitly includes and assumes the skills and tools needed for mid-teaching adjustment are picked up. Following our experiences here, we believe these tools and techniques must be explicitly included in instruction to reach our goals. We recommend explicitly creating activities and content around adjusting to individual students.

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