Strategies to Train and Engage Students in Artificial Intelligence

A White Paper

Completed by Fayetteville State University

and MN Associates, Inc.

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Disclaimer Notice

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Introduction

The overall goal of the white paper project is to conceptualize, design, and implement a model for individually-targeted infusion of Artificial Intelligence (AI) concepts and skills for college students via workshops on AI in future. This document leverages the combined knowledge and experiences of the principal investigators and co-PIs who have previously established two certificate programs in Geospatial Intelligence (GEOINT) and GEODATA and have organized a summer workshop (July 20-24, 2020) on teaching AI techniques at Fayetteville State University (NC).

The proposed document **emphasizes emerging topics in AI** that are **required for scientific and technical work** for computer science and non-CS majors at 2-and-4-year colleges and universities. The foundation for launching this effort has several goals: 1) Fill a growing local and national demand for AI professionals in the area, 2) Align existing expertise and synergies at FSU, and 3) Provide an enriching teaching and learning experience using active learning pedagogical techniques.

Organization and Audience

First, this document outlines the gaps and the need for quality AI education and secondly, it provides a framework for designing diversified, targeted AI workshops that is built upon data findings, lessons learned, and recommendations from the recently concluded AI workshop in July. The intended audience for the white paper are 2-and-4 year colleges and universities and funding agencies.

Importance of AI in Education – Catering to Local and National Demands

In addition to existing data trends from national market analyses on current and future jobs in AI and allied fields, the PI and Co-PIs have also collected their own data to better understand and assess the local demand for teaching AI in colleges and universities. This was done by gathering feedback from faculty members from local community colleges and universities using online surveys, personal correspondence, conducting site visits to colleges and universities, doing lectures, and having follow up conversations.

As part of the dissemination activities of an ongoing National Science Foundation's funded HBCU-Targeted Infusion Project (TIP) grant, the PI and Co-PI conducted a series of lectures at various institutions within the University of North Carolina System including: Winston Salem State University, Elizabeth State University,

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NC A&T State University, and UNC Pembroke. The lectures were attended by both faculty and students from Engineering disciplines and Sciences. The PI and Co-PIs also conducted phone conversations with local officials from Cumberland county (where Fayetteville is located) and the adjacent Bladen and Hoke Counties that are primarily rural and underserved counties of the state.

As a follow up to the visits and conversations, an online survey was administered to assess the biggest need area(s). A total of 39 responses were recorded. The most common response (above 70%) was Artificial Intelligence (AI). The respondents indicated that it is a high priority to educate underrepresented students, students from underserved areas such as rural and/or remote communities, and first-generation college-enrolled students, to help prepare them for future education and the STEM workforce and particularly AI within STEM. In line with the directions suggested by the survey respondents, there are conversations happening at international meetings like the AAAI 2020 Workshop on Equity and Diversity in AI. AI researchers and educators are also researching the discrepancy in the quality of education worldwide, including AI education.

FSU is also in the proximity to Fort Bragg, one of the largest military installations in the country. The military personnel and their spouses make up a significant portion of the student population and contractors seek talented graduates. The students trained in computing and developing AI applications are in increasing demand. Job searches on Google and Glassdoor using simple terms such as "data scientist," "AI," "Fort Bragg," and "Fayetteville," yield in 50+ hits.

Understanding the Barriers and Developing Workshops to Attain the Goals

Numerous barriers prevent students from acquiring AI skills. Underserved communities typically lack resources—equipment such as computers among other tools. While adequate supply of equipment remains a challenge, another gap is limited physical space for conducting hands-on AI activities such as robotics and distributed sensing for decision making. Other challenges are lack of enough trained instructors qualified to teach AI with qualified members leaving underserved communities in search of better opportunities. Because of these reasons, most underserved communities face critical challenges in educating local students in AI and therefore, fail to accommodate the rapidly changing state of art in AI, especially development of new ML models and their applications.

In addition to the above challenges in teaching AI for underserved populations, there are specific challenges related to the limited explainablity of AI models. AI models are very heterogenous requiring a substantial effort to construct an integrated teaching approach. The WP will address these specific challenges by

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developing a taxonomy of explainability of AI processes and use this taxonomy to inform the proposed diversification of the strategy for teaching AI.

Project Goals

Based on the needs assessment conducted by the PI and Co-PIs during a virtual summer workshop on teaching AI held in July, results from the evaluation of the workshop, and understanding the burgeoning needs of AI education, the PI and Co-PIs are proposing a series of similar AI workshops aimed specifically at colleges and universities. These workshops will be individually-targeted to a diverse range of participants including both CS and non-CS students and college and university faculty members at 2-and-4 year institutions. The following are the proposed goals of the workshops.

Goal #1: Provide AI knowledge and skills to college students

Understanding AI – Exposing students to the frontier of AI knowledge–problems & benefits including AI Ethics, and Accessibility *General Technology Skills* – developing and applying AI computing frameworks including *Cloud computing* *Programming skills: Python with AI libraries* – Concepts to implementation. (Different levels of exposure depending on whether they are CS or non-CS students.)

Goal #2 Provide tools and training strategies to college and university faculty members

Pedagogy – Teaching methods to extend inquiry-and project-based approaches and ways to integrate AI computer coding in teaching methods *Technology* – Computing resources and how to compute including *Cloud computing* - Ready access to AI computing *Programming in Python and AI libraries*

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Machine Learning Explainability

Explainability is a growing area of research in ML[1]. Most of this research is oriented towards explainability as an indicator of limitations of ML models in various disciplines. This concept of ML explainability is strongly related to the educational "explainability." In order to design the individually-targeted AI workshops, the PI and Co-PIs have extracted from the literature a taxonomy of explainability components that directly relate to the educational applications and outcomes to help construct educationally-oriented ML "explainability."

The overall goal is to identify the level of "explainability" for various ML processes to match the most appropriate pedagogical methods. **An important characteristic of the workshop plan is to emphasize diversified AI content and teaching methods that are responsive to the needs of learners**.

Several core elements of each ML process and the taxonomy of the "explainability" of ML processes in a broader sense are presented in the table below. According to this classification, "transparency" is the first component and it addresses the fundamental issue of understanding any ML process. In a basic ML process, a model is learned from the given input data and with a specific learning algorithm. Then, in the next phase, the output results are computed using the learned model. Transparency of an ML process can therefore be further classified into the transparency of an overall process structure and function, the transparency of individual process components, the transparency of the learning algorithm, and transparency of how the specific solution is obtained by the algorithm. This document refers to these four transparency categories as shown in Table 1 as **process transparency, component transparency, transparency of learning algorithm, and transparency of testing algorithm.**

Informally, full transparency is the opposite of the "black-box" approach, where using an ML model to perform predictions is the main goal, but the question of how the model outputs its predictions is left unanswered. Transparency thus indicates the level of understanding on how the model actually works. Transparency was explained further by referring to simulatability (considering the entire model) decomposability (considering individual components) and algorithmic transparency for the learning and testing algorithm. All transparency categories determine how well each component's function and structure can be explained in understandable terms to a human.

The analysis of the role of hyper-parameters is also important in order to consider all ML process complexities. Hyper-parameters can determine general model structure, components, optimization algorithm, learning rate, and the size of stochastic sampling, and are often chosen in a heuristic fashion (Roscher, et al, 2020). Due to the possible presence of several local minima, the solution is usually not easily reproducible;

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therefore, these decisions are not transparent. They can be considered as part of the transparency of the process, or associated with the learning algorithm. Transparency of ML processes is an important part of student learning knowledge since this knowledge is needed to optimize the models with respect to high accuracy. Recently there is also growing need to provide the explanation of output results with respect to domain knowledge (Ribeiro, Singh, and Guestrin, 2016).

In addition to “transparency,” another core element of each ML process is identified in Table 1. This category is titled “explainability for domain knowledge” and it requires techniques to discover the underlying reasons for the ML to produce specific results. The explanability of a complex ML process can be improved by using simpler models with only less accurate result. Traditionally, decision trees were used for the explanation of results. More recently the model-agnostic module LIME (Local Interpretable Model-Agnostic Explanations) by Ribeiro et al. was proposed. In the latter case, feature importance can be detected by local linear proxy model in the neighborhood of a focused data.

Table 1. Taxonomy of AI Processes Explainability

Model/ Algorithm	**Transparency Of Whole Process**	**Transparency Learning Algorithm**	**Transparency Testing Algorithm**	**Transparency Hyper- Parameters**	**Explainability for domain knowledge**
Linear Regression	YES-Function YES-Structure	YES-Function YES-Structure	YES-Function YES-Structure	YES-Function YES-Structure	Easy
Decision Tree	YES-Function YES-Structure	YES-Function YES-Structure	YES-Function YES-Structure	YES-Function YES-Structure	Easy
SVM	YES-Function No-Structure	YES-Function No-Structure No-HyperPar	YES-Function No-Structure	NO-Function NO-Structure	Easy
Generic NN	YES-Function YES-Structure	YES-Function No-Structure	YES-Function YES-Structure	No-Function YES-Structure	Difficult

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Generic Convolutional Networks	NO	YES-Function No-Structure No-HyperPar	Partial	Partial	Moderate
Generic NL Deep Learning	NO	NO	NO	NO	Moderate

The educational content analyzed here, namely ML processes, is diversified in terms of explainability as shown in the Table 1. Such content is significantly different from content in other areas/disciplines and making the educational process effective requires special efforts. Often times, ML processes cannot be easily explained and the user has to deal with "black-box" models. Mapping the hard to "explain" content with the proper pedagogical methods is critical. There are multiple pedagogical approaches to teaching various algorithms, procedures and rules developed for the "black-box" or "gray box" approach.

POGIL as a teaching method to address AI teaching challenges

The Process Oriented Guided Inquiry learning (POGIL) teaching technique will support the PI and Co-PIs' efforts and help them design hands-on student activities in AI education. They will map / align the Explainability (Table 1) into the POGIL teaching method. As a result, they will be able to choose the best teaching method instead of applying one solution that may not fit all.

The Process Oriented Guided Inquiry learning (POGIL) teaching technique will be accommodated for both general ML training and specialized AI applications such as in Forensic Sciences. As a pedagogical approach, POGIL allows students to socially construct knowledge through iterative cycles that include three steps: exploring a model, inventing a concept, and applying the resulting ideas.

A growing body of research indicates that relative to lecture-based approaches, POGIL supports student learning more effectively. It allows for a structured approach that requires participants to work in self-managed or regulated teams to explore content, ask questions, solve problems, conduct analysis, record the proceedings, and cooperate to draw valid conclusions. While there are any number of student-centered active learning classroom techniques, POGIL is unique in that it makes students responsible for their own learning, in collaborative teams, so it helps them develop group process skills while they are gaining content knowledge.

Research on POGIL has shown increases in students' learning outcomes, especially in Chemistry, however, there is still a knowledge gap behind assessing the attitudinal factors and the mechanisms behind those

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changes. In one recent study conducted on undergraduate students enrolled in General Chemistry I in Fall across seven sections by Vincent-Ruz, Meyer, & Schunn (2020), found that the four out of the seven sections that used POGIL instructional method (N=809) compared to traditional teaching method (N=543), students in the POGIL method class showed higher chemistry identity, competency beliefs, and chemistry grades. Furthermore, performance in General Chemistry I appeared to be a core mediator of all the observed differences in General Chemistry II where students in the POGIL condition still performed better and had higher chemistry-related attitudes.

Within the POGIL methodology, the PI and Co-PIs use an AI platform called Google Colab (hosted by Jupyter notebook service). The main intent behind using POGIL technique was to enable workshop participants to learn and work in teams, collaborate to understand a concept and solve a structured problem or set of questions rather than being given the content via a lecture by a teacher.

In sum, the POGIL approach includes: 1) Faculty generated-model and related content and 2) Specific problem or defined set of questions for small groups to solve/answer with little guidance from the facilitator.

Previous Grant-Related Work for Building the Next AI Workshops

Fayetteville State University (FSU) completed its second year of implementation of the HBCU-UP award, Targeted Infusion Project: Developing Geospatial Data Analytics Certificate Program (Award No. #1818694). In summer 2020, the supplemental funding was used to host a week-long workshop titled, *Strategies to Train and Engage Students In Artificial Intelligence* brought together over 40 educators and industry professionals from across the state (NC) who learned to use new tools and strategies to teach AI to their students.

The virtual AI workshop held on July 20-24 brought together over 40 individuals that included: K-12 educators, faculty from community colleges and university, and industry professionals to address the above mentioned local challenges in STEM education and help set a roadmap for future education and workforce training efforts by the PI and Co-PIs at FSU and beyond.

The organizing committee comprised PI, Dr. Sambit Bhattacharya, who was supported by Co-PIs, Drs. Bogdan (Denny) Czejdo, and Valentin Milanov, an administrative staff member, a research technician/assistant, and three graduate-level students. The workshop was evaluated by MN Associates, Inc. (MNA) a woman-owned K-20 research and evaluation firm based in Fairfax, VA.

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Procedures

The PI, Co-PIs, and MNA co-developed an online participation interest form (pre-survey) that was sent to various UNC system colleges, universities, and high schools to help recruit workshop participants. Questions related to demographic questions as well as prior/current knowledge of AI topics such as Artificial Intelligence, Regression, Decision Tree, and Artificial Neural Networks were posed. Upon completion, the PI extended a formal e-invite to the participants in preparation of the workshop.

A post-survey with the same questions in knowledge gained as a result of attending the workshop in Artificial Intelligence, Regression, Decision Tree, and Artificial Neural Networks were posed in addition to a series of multiple-choice and open-comments questions related to each day's sessions such as Regression, Decision Tree, and Artificial Neural Networks.

Since the focus of the white paper is to enhance AI education among CS and non-CS students at community colleges and universities, the team is including data on only these two groups. A total of 19 participants engaged in all sessions offered at the AI workshop. Of these, only one of them were from a community college and 18 from various universities. All of them were offered $500 stipend upon completing all the activities. Below is a list of affiliation of the participants.

Table 2-Affiliation of Participants at AI Workshop

Participant Affiliation	N
Fayetteville State University	6
Elizabeth City State University	5
North Carolina A&T State University	3
Forsyth Technical Community College	1
Johnson C. Smith University	1
UNC Chapel Hill	1
UNC Charlotte	1
Winston-Salem State University	1

In the pre- and post-workshop surveys, the participants were asked to rate on a 5-point Likert scale (Low to Very High) the level of their understanding of four topics- Artificial Intelligence, Regression, Decision Tree, and Artificial Neural Network before and after the workshop. The results are summarized below.

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Artificial Intelligence

The only participant from the community college did not think their understanding of artificial intelligence changed after attending the workshop. However, the median rating among the participants from universities increased from 3 (before the workshop) to 4 (after the workshop). Also, see the percentage points change in understanding from pre-to-post workshop.

Figure 2: Pre-and-Post Workshop Ratings on the Understanding of AI

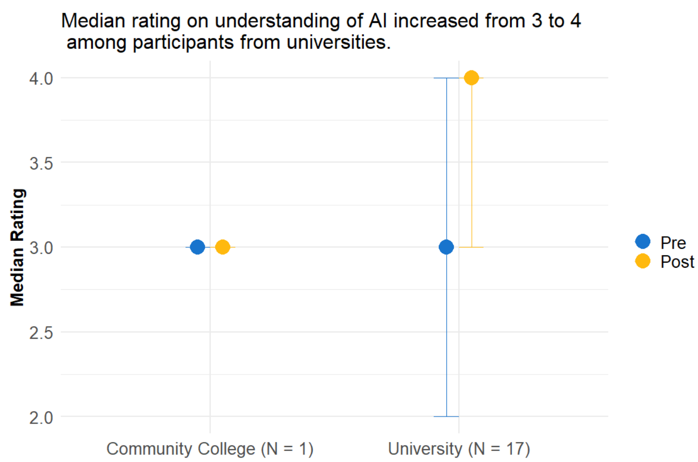
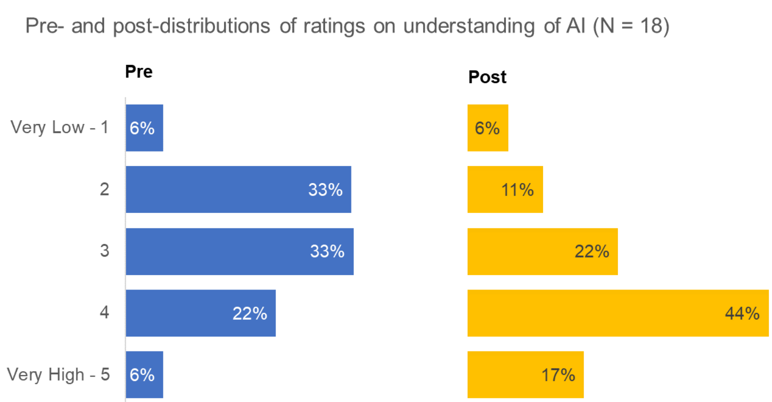


Figure 3: Pre-and-Post Distribution of Rating on Understanding (Percentage Change)



Regression

The participant from the community college reported that their understanding of artificial intelligence improved after the workshop. However, the median rating on the understanding of the topic among the participants from universities remained unchanged at 4 after the workshop. Also see the percentage points change in understanding from pre-to-post workshop.

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Figure 4: Pre-and-Post Workshop Ratings on the Understanding of Regression

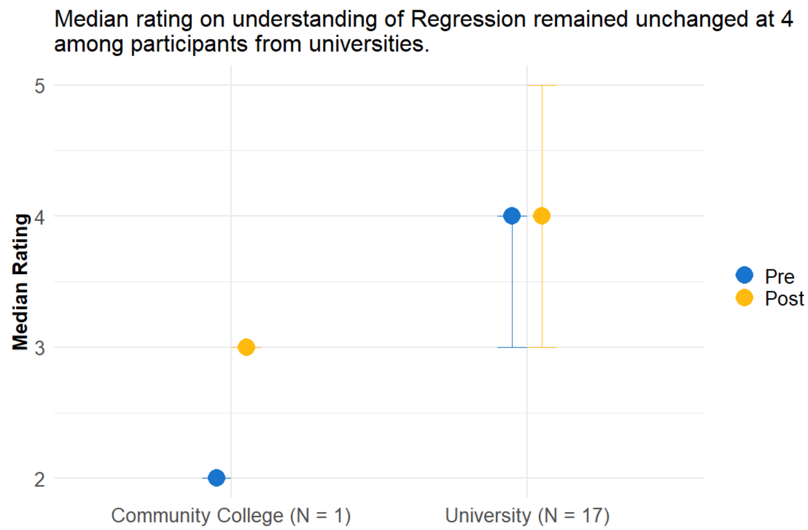
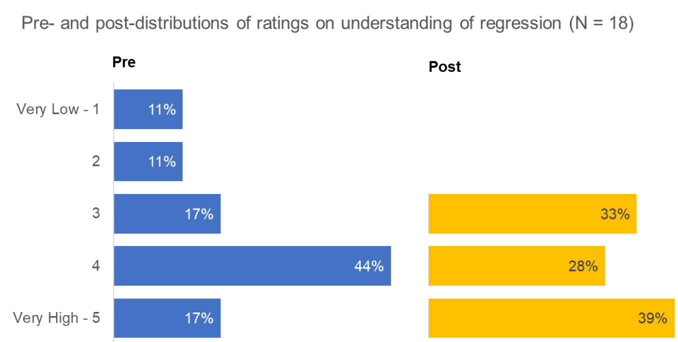


Figure 5: Pre-and-Post Workshop Ratings on the Understanding of Regression (Percentage Change)



Decision Tree

The participant from a community college reported that their understanding of decision tree improved after the workshop. Also, the median rating on the understanding of the topic among the participants from universities increased from 3 (before the workshop) to 4 (after the workshop). Also see the percentage points change in understanding from pre-to-post workshop.

Figure 6: Pre-and Post-Workshop Ratings on the Understanding of Decision Tree

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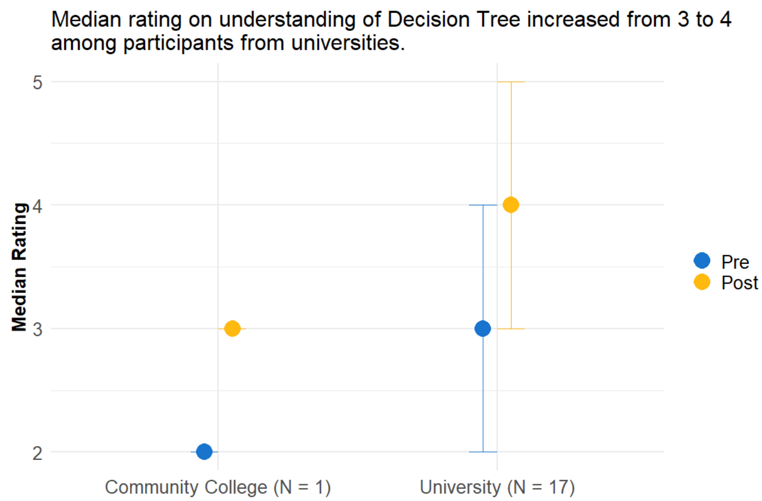
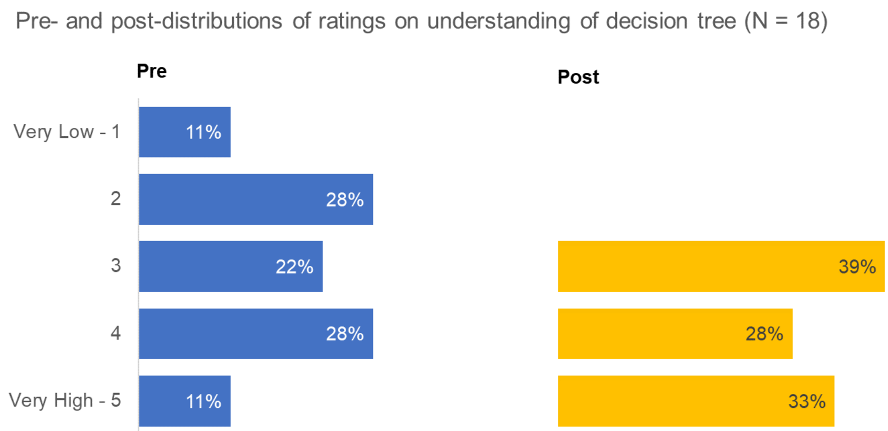


Figure 7: **Pre-and-Post Workshop Ratings on the Understanding of Regression (Percentage Change)**



Artificial Neural Network (ANN)

The participant from a community college reported that their understanding of decision tree improved after the workshop. The median rating on the understanding of the topic also improved among the participants from universities from 2 (before the workshop) to 4 (after the workshop). Also see the percentage points change in understanding from pre-to-post workshop.

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Figure 8: Pre-and-Post Workshop Ratings on the Understanding of ANN

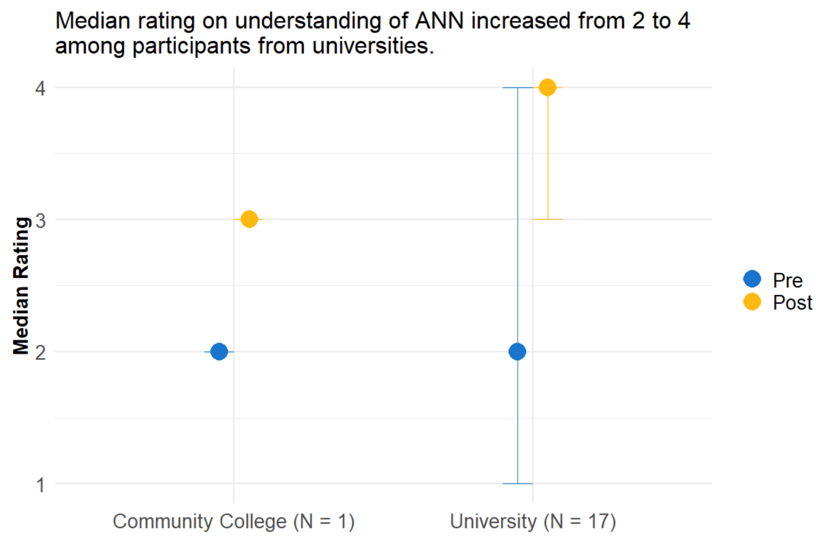
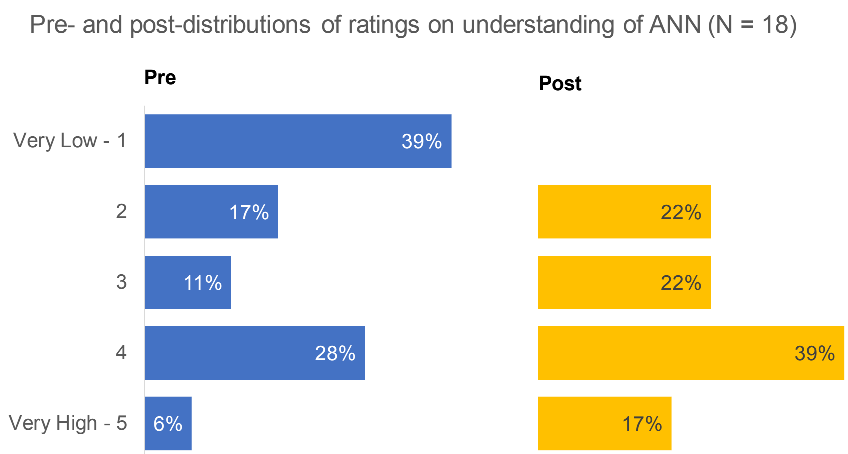


Figure 9: Pre-and-Post Workshop Ratings on the Understanding of ANN



The participant from a community college reported that their understanding of decision tree improved after the workshop. The median rating on the understanding of the topic also improved among the participants from universities from 2 (before the workshop) to 4 (after the workshop).

Other Survey Responses

In this section, responses of the participants on various items related to the workshop are summarized. Participants rated their experiences on a 3-point Likert scale - “completely adequate/very satisfied”, “somewhat adequate/satisfied”, “not at all adequate/satisfied.”

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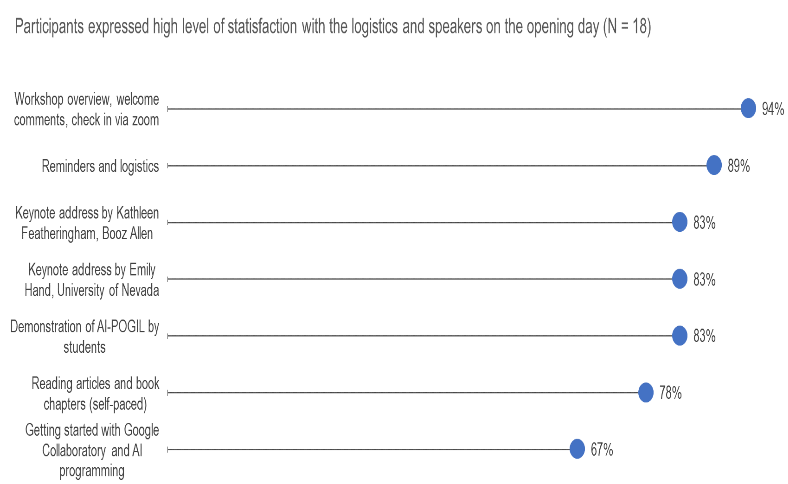
Day 1 - Welcome, Keynote Address, and Introduction to Google Colab

The post-workshop survey indicates that the majority of the participants (on average 85%) were highly satisfied with the welcome session, workshop logistics, and keynote speakers—Emily Hand, Ph.D. and Kathleen Featheringham, M.S.

Figure 10: Day 1 (All Sessions)-Percentage of Participants Reported **"Completely Adequate/Very Satisfied"**



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Participant comments included:

"Adequately paced all day workshop with genuine breaks and very informative keynote address."

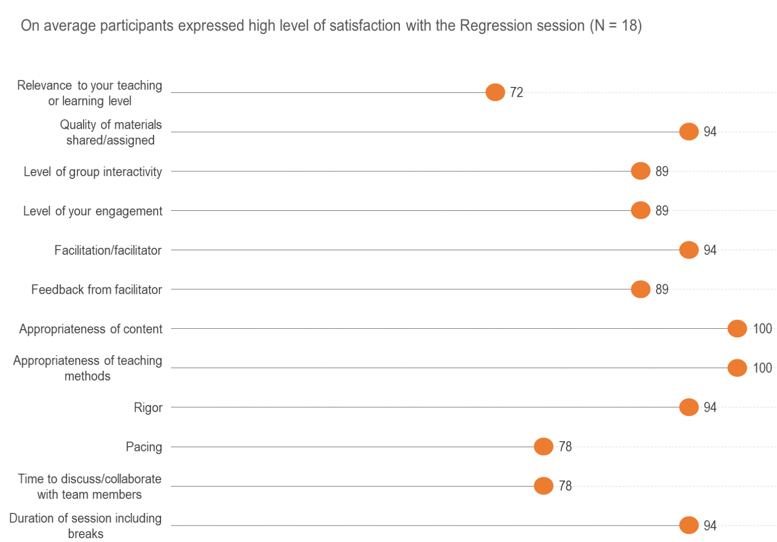
"Well done!"

Day 2 - Regression

On Day 2, participants worked on activities related to estimating and interpreting linear regression models. The post-workshop survey asked participants about their experiences with various aspects of this session. The figure below shows the percentage of participants who found various aspects of the session were completely adequate.

On average, the participants from universities expressed higher levels of satisfaction with the session than their peer from the community colleges. Except for the performance of the facilitators, every other item sees a large difference between the two groups. Relevance of the topic to one's teaching and prior familiarity with both content and technology like Google Colab appeared to have contributed to varied experiences in the groups.

Figure 11: Day 2 (Regression)- Percentage of Participants Reported "Completely Adequate/Very Satisfied"



University participants comments:

"Students can have the option to work on their own data sets and work individually first. After everyone finishes, then they can discuss."

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"Exceptionally brilliant session!!"

"Really learned a lot from this well facilitated session."

"The session was great but a fair amount of heads up—what's coming next--- would have been helpful to prepare and read."

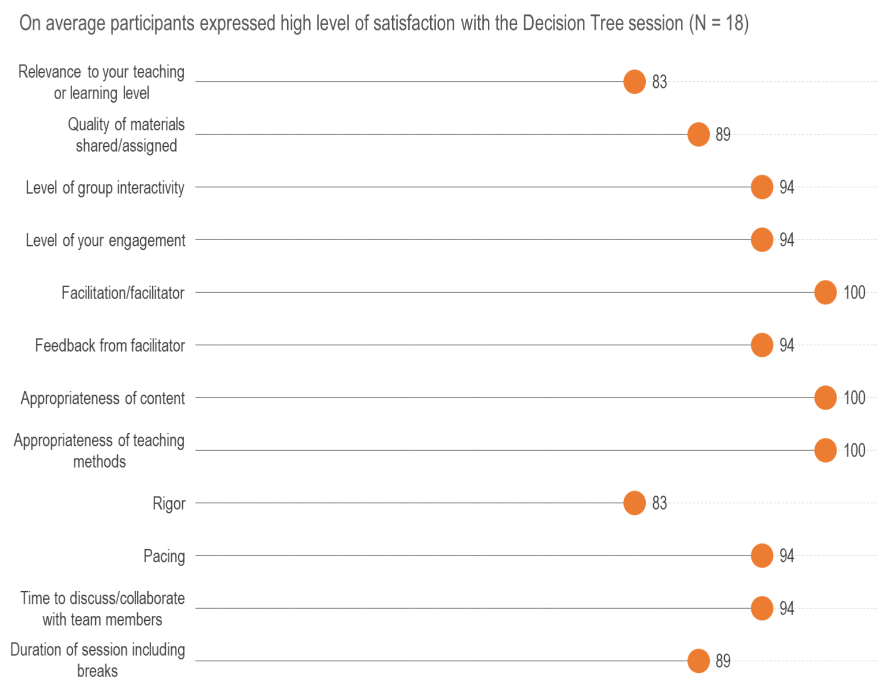
"Given the varied degree of participants' prior knowledge and background, the experience was varied. The sudden introduction of ML without any background was difficult to comprehend."

Day 3 - Decision Tree

On Day 3, participants worked on activities related to running decision tree ML models. The figure below shows the percentage of participants who found various aspects of the session were completely adequate. Consistent with the regression session, on average, the participants from the community college and universities expressed higher levels of satisfaction with the decision tree session.

Figure 12: Day 3 (Decision Tree) - Percentage of Participants Reported

"Completely Adequate/Very Satisfied"



University participants comments:

"It was much better than regression."

"It is a good method to divide and analyze the problem and create categories."

"You may want to add more explanations for figures. Some of them are hard to interpret."

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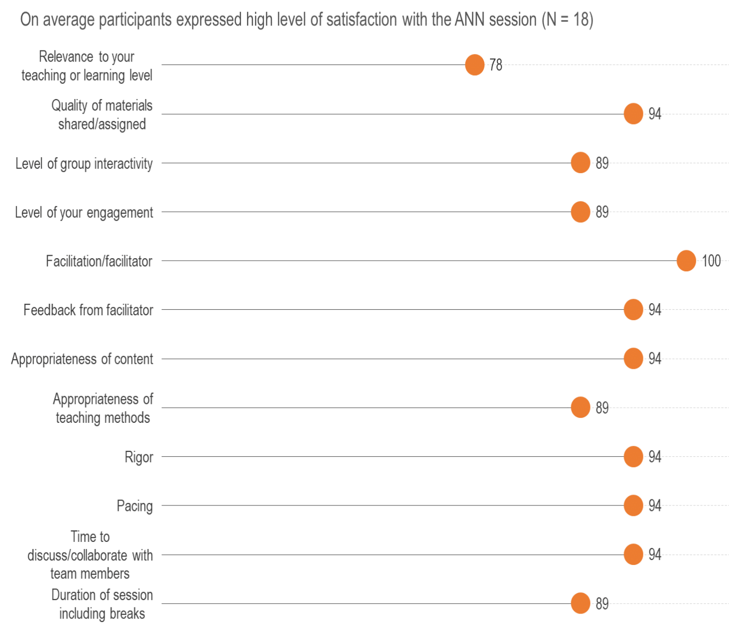
Day 4 - Artificial Neural Network

On Day 4, participants worked on activities related to artificial neural network models. Again, the figure shows response patterns very similar to the previous two sessions. Overall, the reflections on the session noted by the participants were positive.

Figure 13: Day 4 (ANN) - Percentage of Participants Reported
"Completely Adequate/Very Satisfied"



University participants comments:

"For the first time I have learned what ANN really is. It was good to see it in action and learn at the same time."

"A little difficult for the beginners. Some easy techniques could have been utilized for orienting the beginners."

"This was the most valuable activity for me to understand the concept of neural networks, especially how the weights really work. Of course, the session was an excellent opportunity to learn and network."

Day 5 - Keynote Address and Participant Presentations

Day 5 began with the final keynote address by Dr. Sudipta Dasmohapatra, faculty at Duke university, followed by a presentation by individual participants. The post-workshop survey asked participants to rate various sessions. Overall, the participants appeared to be highly satisfied with the sessions. Participants were

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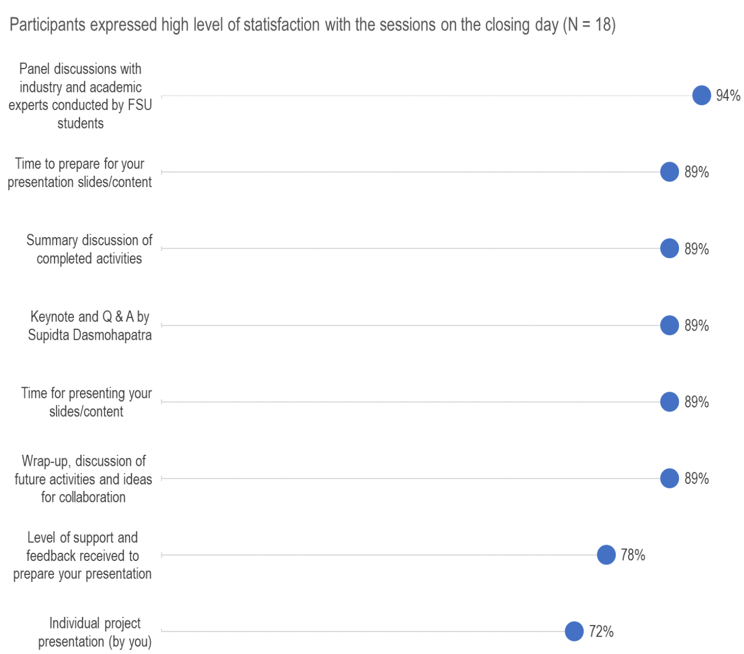
given the flexibility to present either their own codes or discuss a topic of their choosing that they learned from the workshop. Only 2 out of 19 participants chose to present a code.

Figure 14: Day 5 (Closing Sessions) - Percentage of Participants Reported

"Completely Adequate/Very Satisfied"



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Participants comments:

"Excellent keynote and great to hear presentations from all participants."

"Having so many panels and keynote speakers back to back became a bit cumbersome."

"Increase time per session and a smaller number of sessions."

Open-Ended Questions

A set of open-ended questions were posed at the end of the post-survey that focused on items related to the extent to which the participants learned from their experience as a recorder, facilitator, or an evaluator during the Days 2-4 interactive sessions and how the sessions could be improved in future followed by how they participants intended to implement some of the POGIL teaching strategies and/or software tools (e.g, Jupyter notebooks/Colab) in their classroom setting.

First, to the question on their role as a recorded, facilitator, or an evaluator, 15 responses were collected. Those who were in the role of a facilitator or a back-up, their responses were mostly positive

Facilitator - my experience was excellent - even though I had many interruptions due to other staff within my building needing my attention - my backup - Reema - was ready to step right in - I felt Denny was an excellent leader and kept us moving forward.

I was a back-up facilitator and recorder. I experienced better understanding in these roles as compared to being just a participant. As a facilitator, you have to comprehend the information as you ask questions; thus, you put more conscious effort and ask questions if needed that otherwise you may be shy about. As a recorder, again, you have to comprehend the responses before you record them. I believe there are no changes needed for these positions.

A few recommendations for change(s) were also made

Very good experience and only if there are more time and prior knowledge.

I was a facilitator and enjoyed leading the group. I could improve by knowing more about the topics before facilitation.

Please allow everyone to see the information clearly before documenting it.

Those who were either a recorder or an evaluator had similar positive experiences and made some suggestions for change(s):

I was an evaluator-my experience was fine. I saw no need to change anything.

I was a recorder and an evaluator. I think recorder and the facilitator should be the same person or better yet, each participant should be a facilitator and recorder on separate datasets. Then record their own session.

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I felt responsible and it kept me more alert and active during the session. It may have helped to go over it prior to the actual session.

Colab was not the best software to use in my opinion (as a computer science student we don't really use colab but we use JGrasp, Octave, MetLab, or StudioCodeX)

To the question, which aspects of the workshop are you likely going to use in your teaching and how, several responses were gathered around teaching POGIL and AI concepts and misconceptions to students, teaching other educators on campus, using Colab and Jupyter notebook, decision tree and plotting features. Some pertinent responses are

I will use POGIL. The use of role assignment - and I am currently looking at how some of my curriculum has changed and how I can use electronic notebooks or something similar to help my student groups stay on target/track.
I will use Colab and the use of a facilitator, recorder, and evaluator in some of my classrooms.

I will propose and teach a Data Science course. I may modify and use Colab notebooks there.

Depending on the curriculum that I am given for my Cybersecurity and Networking classes that I will be teaching I will be using a great deal of it. I will at least reference the book and Artificial Intelligence as a whole, it is all tied in together.

For the online data science certificate program at UNC I have already proposed the use of Google Colab tools and POGIL methods for content development.

To the next question, based on your learning from the workshop during these past days, is it likely that you will apply any of the topics and/or concepts when you return to your classroom? If yes, what are those and how do you plan to use them? If not, why not, responses were quite similar to the above question. They are

Maybe, ANN can be implemented.
Yes, as required. In particular the book and Colab. I work with startup founders, so not a typical classroom environment.

Depending on the curriculum that I am given for my Cybersecurity and Networking classes that I will be teaching I will be using a great deal of it. I will at least reference the book and Artificial Intelligence as a whole, it is all tied in together.

Yes, I can use regression and decision tree in my classes. Then, we can compare engineering vs. business students' performance.

I plan to use similar notebooks for LR, DT, and ANN later in a new course that I will teach. I have not yet finalized the course outline.

In relation to the extent to which the participants are likely to apply the POGIL technique in their teaching when they return to their classroom, a majority of the responses were No, Unsure (at this point), It depends,

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and Maybe. Some stated reasons were: (I would like to) gauge the feasibility and applicability of POGIL in the classroom setting on the lessons/modules I am teaching before using it; and not fully understanding what POGIL is or does in a classroom setting. Other comments where participants expressed an interest to use POGIL method were

It will be a great way to get away from the traditional video lecture and assessments for learning.

I will guide my students through the processes of how artificial intelligence can be used in research.

As long as I am allowed to, I will at least introduce it to my students at least as a knowledge base for them.

Definitely! It's always exciting to have a new tool in the tool box.

I haven't tried it before. It's a student-centric approach and
I'll consider using it.

A majority of the participants (90%) stated that they are excited/ enthusiastic to a large extent about applying what they learned in the workshop (content and pedagogy) in their teaching/instruction.

General Takeaways and MNA's Observations

The workshop was organized and conducted well. About 90% of the participants reported that to a large extent, they see the benefits of using cloud computing in their academic settings. About the same percentage of participants also reported that to a large extent, they understood the differences between learning algorithms and software and they would be able to explain to their students the concepts of AI learned from the workshop. About 70% of the respondents reported that their awareness of how AI can be misused to spread fake news and information has increased to a large extent.

In their observations, MNA noted that the POGIL technique was being implemented with fidelity on all the three days when participants were learning/working on Regression, Decision Tree, and ANN concepts. Although, there were some initial technical glitches due to connectivity or device issues, the teams were able to work together.

The word cloud below summarizes the participants' responses about main takeaways from the workshop. Artificial Intelligence and Google Colab are the topics most frequently mentioned by the participants.

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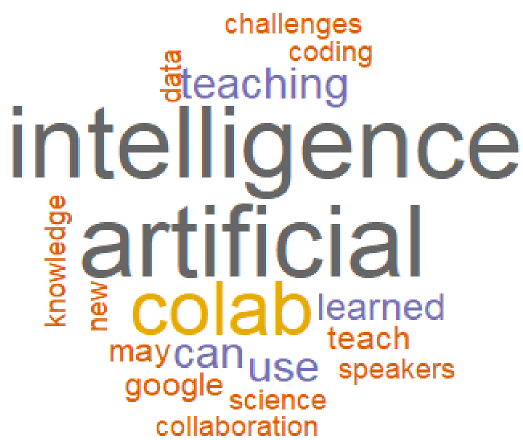
The majority of the participants also noted that they are open to apply technologies like Google Colab and POGIL, to teach AI in their institutes.

Figure 15: Word Cloud of Three Main Takeaways from the Overall Workshop



Lessons Learned - Areas of Enhancement

Participants reported that their understanding of ANN improved the most after the workshop. The median rating on the understanding of the topic also improved among the participants from universities from 2 (before the workshop) to 4 (after the workshop). This is consistent with the categorization table that shows opposite to common knowledge that the level of explainability of ANN in terms of structure is high.

Based on MNA's observations, post-survey responses from participants, and feedback provided during the individual presentations, the following areas of enhancement are suggested:

- Design of future workshops could be adapted to participants' skill level(s) and relevance. For example, participants from CCs and Universities have different needs and technical exposure to advanced topics such as those presented in the workshop. The workshop contents could be better designed and organized to meet these needs.
- Conducting a content-specific needs assessment before the workshops could be beneficial in customizing the content and format of the sessions.
- Basic preparatory materials including Melanie Mitchell's book on AI and presentation slides could be shared with the participants prior to the workshop to allow time for review.
- Create shared Google folders to help track individual participant's performance on Days 2-4.

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- Assign reading(s) directly related to the hands-on activities to enable easier understanding of concepts.
- Technical challenges with software, internet connection, and device(s) are inevitable to occur with online delivery, however, it would help to provide clear and guidance prior to the workshop.
- Day 5 could be shortened by reducing the number of individual sessions and include an option of small group presentations.
- Develop a website or webpage on FSU's site to host all the workshop materials for easy access to all participants.
- Use a dissemination mechanism to share these resources with participants and other collaborators.

Reflections of Organizers

There are two major reflections of the workshop that will be addressed in the new project. The first one is the need to individualize instruction and design adaptable POGIL curricular modules. The educational needs of producers and consumers of ML applications are different. The first group needs to get insight and programming skills to be able to implement ML algorithms. For the consumer of ML, there is a need to emphasize the application of ML models and its transparency.

The second observation of organizers is to go through the rigorous assessment and refinement of POGIL modules. Since the proposed document emphasizes emerging topics in AI the well-targeted curricular modules have not been developed yet and significant work on using active learning pedagogical techniques is required and it will continue to be required with evolving ML techniques and approaches.

Next Steps

The next steps for the PI and Co-PIs are to extend existing efforts to deliver training ML for CS and non-CS majors at FSU and other 2-and-4-year colleges and universities, or fund the training of compatible audience of professionals. Cooperation in launching a common effort to fill a growing local and national demand for AI professionals, is also part of the plans.

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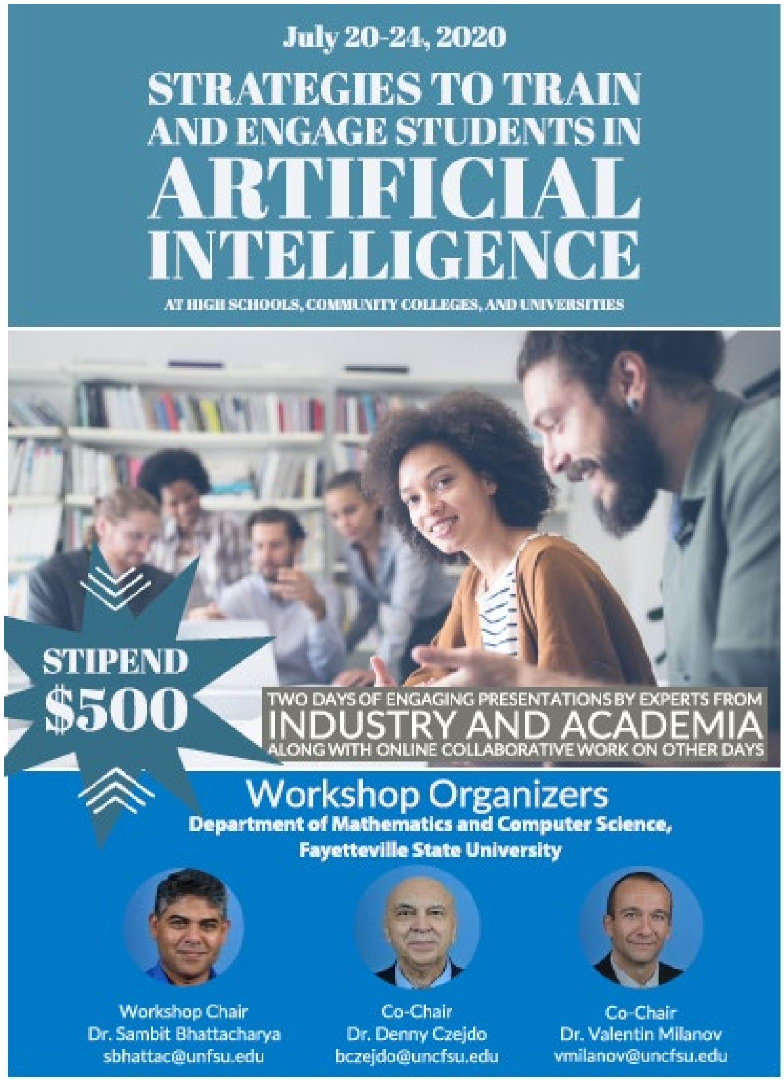
Appendix

Participation flyer



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Agenda

DAY ONE - MONDAY JULY 20^{TH}

Time	Activities
08:45 AM – 09:30 AM	Online check in via Zoom, welcoming comments, workshop overview
09:30 AM – 09:45 AM	Break (10-15 mins)
09:45 AM – 10:45 AM	Keynote and Q&A by Kathleen Featheringham, Booz Allen Inc.
10:45 AM – 11:00 AM	Break (10-15 mins)
11:00 AM – 12:00 PM	Keynote and Q&A by Emily Hand, University of Nevada
12:00 PM – 01:00 PM	Lunch break (1 hour)
01:00 PM – 01:30 PM	Getting started with Google Collaboratory and AI programming
01:30 PM – 01:45 PM	Break (10-15 mins)
01:45 PM – 02:15 PM	Demonstration of AI-POGIL by students
02:15 PM – 02:30 PM	Break (10-15 mins)
02:30 PM – 02:45 PM	Reminders and logistics
Flexible, start at your convenience	Read articles and book chapters which will be given to participants. This is a self-paced activity which may take 2 – 3 hours of time.

DAY TWO - TUESDAY JULY 21^{ST}

Time	Activities
09:45 AM – 10:00 AM	Online check in via Zoom assigned to group, preliminary discussions
10:00 AM – 01:00 PM	Three hours of hands-on training on AI topic: Regression & Teaching Methods. Flexible break times to be decided by group and facilitator. Group 1 (Facilitator: Sambit Bhattacharya) Group 2 (Facilitator: Denny Czejdo) Group 3 (Facilitator: Valentin Milanov)

DAY THREE - WEDNESDAY JULY 22^{ND}

Time	Activities
09:45 AM – 10:00 AM	Online check in via Zoom assigned to group, preliminary discussions
10:00 AM – 01:00 PM	Three hours of hands-on training on AI topic: Decision Tree Learning & Teaching Methods. Flexible break times to be decided by group and facilitator. Group 1 (Facilitator: Sambit Bhattacharya) Group 2 (Facilitator: Denny Czejdo) Group 3 (Facilitator: Valentin Milanov)

DAY FOUR - THURSDAY JULY 23^{RD}

Starting Time	Activities
09:45 AM – 10:00 AM	Online check in via Zoom assigned to group, preliminary discussions
10:00 AM – 01:00 PM	Three hours of hands-on training on an AI topic: Neural Networks & Teaching Methods. Flexible break times to be decided by group and facilitator. Group 1 (Facilitator: Sambit Bhattacharya) Group 2 (Facilitator: Denny Czejdo) Group 3 (Facilitator: Valentin Milanov)

DAY FIVE - FRIDAY JULY 24^{TH}

Starting Time	Activities
09:45 AM – 10:15 AM	Online check in via Zoom, summary discussion of completed activities
10:15 AM – 11:15 AM	Keynote and Q&A by Sudipta Dasmohapatra, Duke University
11:15 AM – 11:30 AM	Break (10-15 mins)
11:30 AM – 12:30 PM	Panel discussions moderated by students
12:30 PM – 01:30 PM	Lunch break (1 hour)
01:30 PM – 02:30 PM	Town hall discussions (open to all)
02:30 PM – 02:45 PM	Break (10-15 mins)
02:45 PM – 03:45 PM	Project presentations by groups
03:45 PM – 04:15 PM	Wrap-up, discussion of future activities and ideas for collaboration
04:15 PM – 04:30 PM	Completion of post-survey

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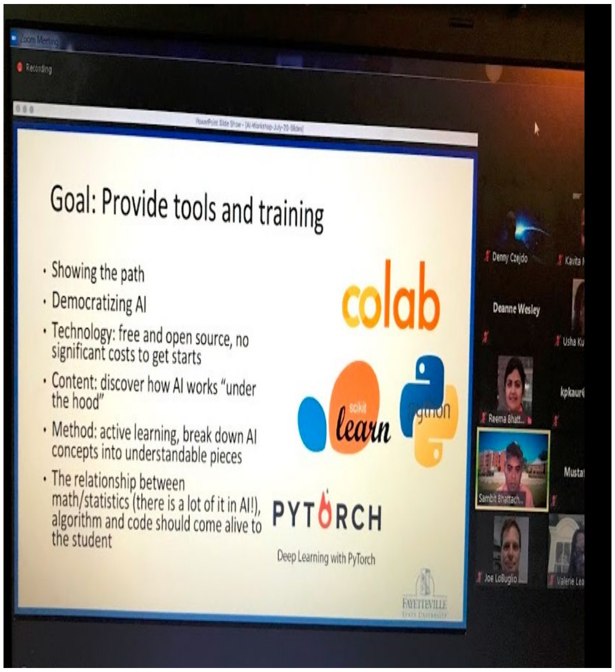
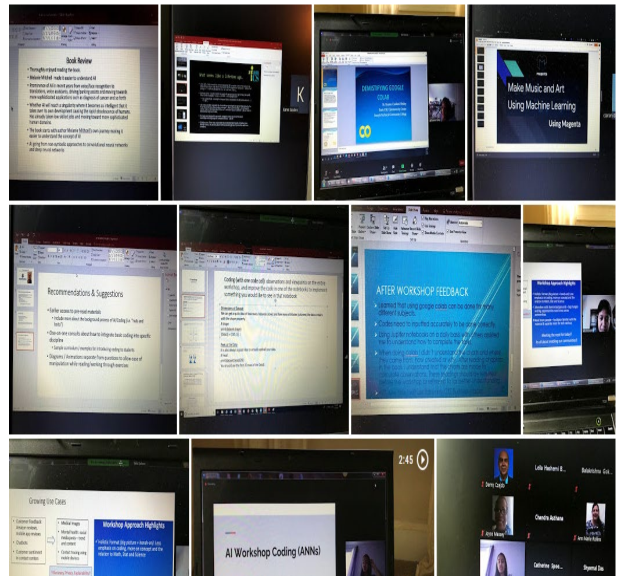
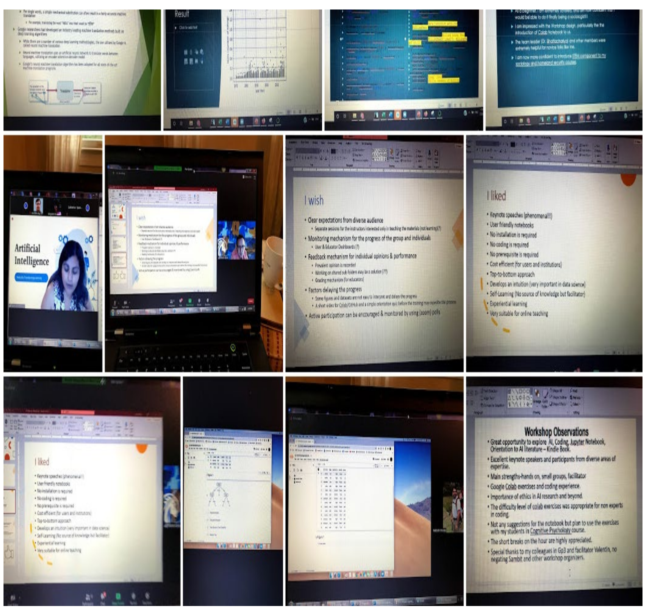
Screen Shots of Select Sessions







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