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GIFTS: An interactive, class-wide activity for gaining an Intuitive Understanding of the Machine Learning Pipeline for All Learning Levels

Kevin William Bachelor, University California, Santa Cruz

Kevin Bachelor is a fourth year Computer Science student at University of California, Santa Cruz. Kevin taught Machine Learning as a student instructor for 2 years with the Lead by Design Program under Professor Tela Favaloro after finding his love for teaching by leading and teaching with the University's AI club. His teaching propensity for teaching ML comes from his fascination with the topic, and a background in acting. He continues each individually as well with a theater minor, and continued research in Machine Learning for Molecular Dynamics with Professor Razvan Marinescu. He will soon be continuing on as a PhD at UCSC under the same lab doing development in the intersection between machine learning and computational chemistry for drug design.

Anthony Furman, University of California, Santa Cruz

Anthony Furman is a Robotics Engineering undergraduate student and research assistant at the University of California, Santa Cruz. He joined the Lead by Design program Fall 2024 and designed the Introduction to Machine Learning class, then teaching it for two years. He has applied his interest in both Machine Learning and Robotics at the UCSC HARE Lab, where he works on designing RL algorithms for robotic systems.

Dr. Tela Favaloro, University of California, Santa Cruz

Tela Favaloro is an associate teaching professor for the Baskin School of Engineering at UCSC where she works to establish holistic interdisciplinary programming centered in experiential learning. Her Ph.D is in Electrical Engineering with emphasis in the design and fabrication of laboratory apparatus and techniques for electro-thermal characterization of sustainable power systems as well as the design of learner-centered experiential curriculum. She is currently working to develop an inclusion-centered first-year engineering program in hands on design and problem-based learning to better support students as they enter the engineering fields.

GIFTS: An interactive, class-wide activity for gaining an Intuitive Understanding of the Machine Learning Pipeline for All Learning Levels

This GIFTS paper presents *Becoming an ML Model*, an introductory and computer-independent activity to experientially teach students about the train-test-use pipeline for Machine Learning (ML) models in a collaborative classroom environment. This ~45 minute activity is meant to run during the first day or two of class to help students develop an intuitive understanding of what an ML model does during the train, test, and use stages of the ML pipeline, why each stage is important, and to serve as a fun and exciting icebreaker that brings students together.

Motivation

Machine Learning (ML) skills have seen a sharp increase in demand over the past ten years, and university education is failing to keep up with the growth. Many ML skills, including simply the ability to understand Machine Learning models, would see a 70% deficiency among workers compared to what was needed in the industry by 2024, while vacant positions for AI developer jobs have jumped threefold in the past ten years [1][2]. Unfortunately, current higher education techniques to teach ML compound this issue. Much of modern Machine Learning education approaches the subject from a mathematical point of view and therefore requires significant prerequisite training, as evidenced by an analysis of thirty course offerings from a list of the "Top AI Schools" [3], all of which require math and programming prerequisite courses. Thus, many interested students are barred from ML classes until after they complete the math-heavy prerequisite chain of courses. Often this means waiting until 3rd or 4th year, leaving little time to apply and build their knowledge and skills before graduation.

We believe that there is a more accessible path for learning ML, and it starts with a more holistic and conceptual underlying understanding of ML that may later be built upon. *Becoming an ML Model* helps to fill this gap in accessible machine learning education as an experiential introduction to the core ideas of Machine Learning. Currently deployed in an introductory, lower division Machine Learning course with no prerequisites [4], the activity serves as the opener for the first day of class and is the first step in establishing an accessible and participatory classroom environment.

Objectives

This participatory activity aims to build learners' holistic understanding of Machine Learning and the associated train-test-use pipeline by transforming the classroom and its occupants into an ML model. The class, acting as an ML model, would go through each stage of the train-test-use pipeline on an image dataset given in Appendix A.1, thereby using physical participation and collaboration to act out the process of how machines actually learn. *Becoming an ML Model* requires no prerequisite knowledge and is appropriate for middle school to university settings.

Implementation

Becoming an ML Model is a three-stage activity followed by a recap to cement the main points covered. During the activity, the students become an ML model by performing the processes of train, test, and use on a set of images. From a facilitation perspective, the activity predominantly consists of showing students images then recording their guess for a number associated with each image. For the implementation presented here, the students are guessing the *worth* of the object depicted in each image, but the students do not know that. *Becoming an ML model* requires very little in the way of additional physical materials, instead relying on staple classroom items such as, a) a visible timer, b) a large whiteboard/chalkboard to record classroom responses, c) a monitor or projector to display the images and d) (optional) individual whiteboards and markers (1 per group). Digital teaching materials are provided in Appendix A.1.

1. Training Stage: (15min)

Becoming an ML Model opens by instructing the students that they will be guessing, together as a class, the corresponding number for each image shown and after will be given the correct number. This explanation is clearly missing the key point of *what they are guessing* and therefore can leave students confused. It is the role of the teacher to help assuage as much confusion as possible and shift their reaction from confusion toward excitement for discovery. Details on fostering excitement during this stage of the activity can be found in Appendix B.1.

Guess, Discuss, Answer, Learn: We then enter the actual *training* of the class-as-an-ML-model. Students are shown an image and asked to discuss then decide what the corresponding number should be. This phase prompts the students to do the following:

1. “Come up with an initial guess, write it on your whiteboard then hold it up” (5 seconds)
2. “Discuss with the person sitting next to you” (10 seconds)
3. “Discuss with your entire table group (3-4 students) and settle on one number to present to the class” (20 seconds)
4. A random table is called on, and their score is recorded on the large class whiteboard.
5. Instructors then reveal the actual number associated with the specific image, which is also recorded on the large whiteboard next to the class’s guess (as in Table 2, Appendix A.2).

Each step is designed to bring all students into the discussion and foster independent thinking. We further elaborate on why the steps are laid out like this in Appendix B.2.

Repeat for 13+ images. We repeat this process of *Guess, Discuss, Answer, Learn* for a total of thirteen images during the training stage. As students start to figure out the association between the image and the number, their guesses begin to converge and discussions shorten in length. We often shorten or remove the partner step when 30 seconds of discussion is no longer needed. By the end of the training stage, it is important that the class has determined the relationship between the image and the number associated with it. Facilitation strategies to guarantee this outcome can be found in Appendix B.3. Throughout our three iterations of running this activity, all student-cohorts realized they were guessing ‘worth’ within thirteen images (they often call it ‘price’ or ‘cost’); though you may want to have more images available just in case.

2. Testing Stage: (10 min)

Here, we tell the students they are entering the testing stage. They will no longer be learning; we will merely be measuring their accuracy as an ML model. There is no discussion of the link between the image and the number and no mention of whether the training was successful.

Guess, Discuss, Answer: To test the class-as-an-ML-model, the activity is run similarly to Stage 1 for six additional images. However, students are not given the ‘correct’ value until all six images are analyzed as a way to emphasize that they are being tested and no longer learning. The first four steps of Guess, Discuss, Answer, Learn are performed for each, skipping Step 5 where the students are shown the actual value of the image. The exact timing allocated to the discussion step depends on available time and current classroom needs.

Assess: Only after this process has been completed for the six images do we go through each image and give the students the 'right' answers, which we record next to their own guesses on the class whiteboard. We culminate this stage by making an estimate of how "accurate" the students-as-a-model is. Since students have not yet learned the formal ML methods for measuring accuracy, we simply look at their guesses and compare them to the actual correct numbers. For each image, we find the difference between these two values and try to get an approximate average of these differences over all six images (we are calculating the Mean Absolute Error, only they do not know that term yet). For the example given in Table 2 in Appendix A.2, the student ML model tested to be +/-1 of the actual answer; students consistently guessed either one above or below the actual value. The average becomes their model accuracy.

3. Use Stage: (5 min)
After testing, we get into what is frequently considered deployment in the ML world, but in this activity, we refer to it as the *use stage* for simplification. Here, we repeat the *Guess, Discuss, Answer* steps for five images as if they were testing, however, we do not provide their associated numbers at any point during this stage. We simply record their guesses for each image after the now well practiced guessing and discussion steps. After the final image is shown and their final guess is recorded, we tell them the activity has concluded and they will never know the 'correct' numbers for this set of images because there are none. We explain that ML models are eventually being deployed on unlabeled data, just as they were during this stage, and we assume that their guess is within the accuracy measured in the testing phase.

End of Activity Discussion: (10-15 min)
Becoming an ML Model closes with a making meaning discussion. First, we satisfy their hopeful curiosity that the numbers were indeed the *worth* of each image, but we are very careful to clarify that an ML model would never get to know this. Then we unpack some of the deeper concepts through a recap discussion centered around the following learning outcomes:

- Explain how an ML Model learns to approximate an understanding from data
- Describe the order and importance of each step of the train-test-use pipeline
- Understand that a model's accuracy is an approximation from testing
- Compare the way in which humans learn to the way in which models learn.

See Appendix B.4 for tips on running this activity stage and motivating discussion questions.

Finally, the issue of bias in data is brought up, either by the students or the facilitators if the discussion does not get there naturally. While debating their guess for the worth of an image, students often refer back to a previous image's number as a way of calibrating their current guess. Students often will change their guess to a value *they thought was less accurate to real life* but better reflected the patterns of the previous data. Here it should be explicitly pointed out that the students just experienced the tendency of models to *emulate biased patterns in the data, even when they are not accurate to real life*. This parallels how models do not learn objective facts, but merely patterns that exist in the dataset which frequently include bias.

To encourage continued reflection and thoughtfulness on these topics, the next class session opens by asking the students to write a reflection in their notebooks, prompted by two questions: “What were your thoughts on *Becoming an ML Model*?” and “What were the biggest takeaways?” This reflection serves as a refresher to bring these takeaways into the next class.

Assessment

The effectiveness of this activity is assessed by evaluating students’ understanding of the ML pipeline and their ability to explain the purpose of and process behind each stage. Real-time formative assessment occurs during the activity via instructor observations and facilitation. The recap discussion primarily serves to communicate the takeaway messages - the *so what*, reinforcing the learning outcomes. Moreover, the follow-up notebook reflection surfaces learning, post activity. Themes emergent from an inductive analysis of these qualitative items are generally positive for engagement, using words such as “*loved*,” “*fun*,” and "*enjoyment,*" also citing the *clarity* the activity provided. Student-responses additionally took learning a step further, elucidating a deeper understanding not only of the sequence of machine learning, as “*we learnt from the feedback to become more and more accurate,*” but also on HOW machines learn, for example that “*ML needs to know a lot more things and learn because it does not recognize things that we [as people] know*.”

To capture changes to learner understanding of the ML pipeline, we conduct a short pre-post questionnaire (Table 1) wherein the students select and order the applicable steps within the three stages of the ML pipeline given the options of: predict, score, learn, and blank (not applicable). We also ask them to measure their confidence in their own understanding. These same questions are asked again in the first homework assignment, completed after the activity.

Table 1: Student survey results showing their understanding and confidence in the train-test-use pipeline. Pre-post quantitative data shows an increase in both after the *Becoming an ML Model* activity.

Survey Question	**Pre Activity**	**Post Activity**
% Correct responses to ML Pipeline Survey Question	36%	95%
% of Students reporting confidence levels of 4 or 5 (out of 5) in understanding the train-test-use pipeline	13%	76%

Conclusions

College-level education frames Machine Learning as daunting and math-heavy, only available to more advanced students. Our low barrier of entry, introductory activity presented in this GIFTS places the students into the perspective of an ML model, experientially immersing them in the train-test-use pipeline to effectively teach important conceptual learning outcomes for learners with no background. *Becoming an ML model* is a fun, engaging, and collaborative first step toward developing a holistic understanding of Machine Learning for all grade levels.

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Appendix A: Instructional Materials and Examples

1. Instructional Slides for Activity

This activity was built around a classroom-wide analysis of a series of images portraying objects and their corresponding worth. However, the activity theoretically should work using any image set with a visually discernable label, though for the activity to run smoothly, certain considerations should be met. These are described in Appendix B.5. We provide slides for the image set we used here:
https://docs.google.com/presentation/d/14GU6P-mmTw8ypXQHE5a2JegHUFzltXLIg9joNkIo_6g/edit?usp=sharing

A few examples of the content in these slides are provided below in Figure 2, and the recap slides are provided afterwards in Figure 3.

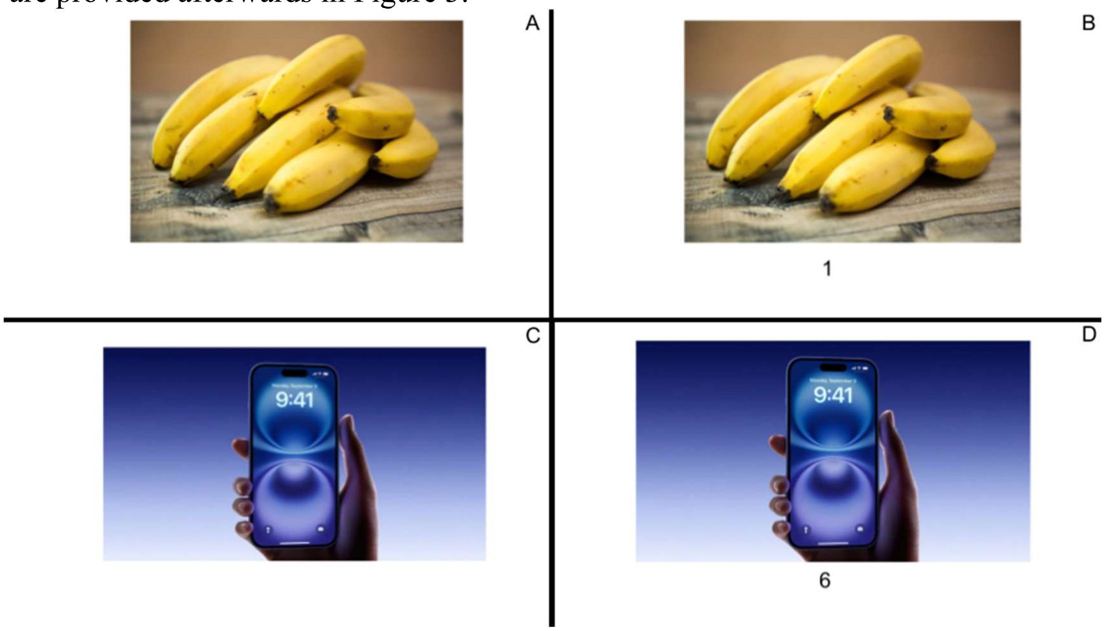

Figure 2: Four selected slides from our image/ worth dataset shown with and without their corresponding numbers, as used in our activity. Sequentially, slide B follows A, and D follows C; the associated value of each object is revealed after the students have had time to guess it.

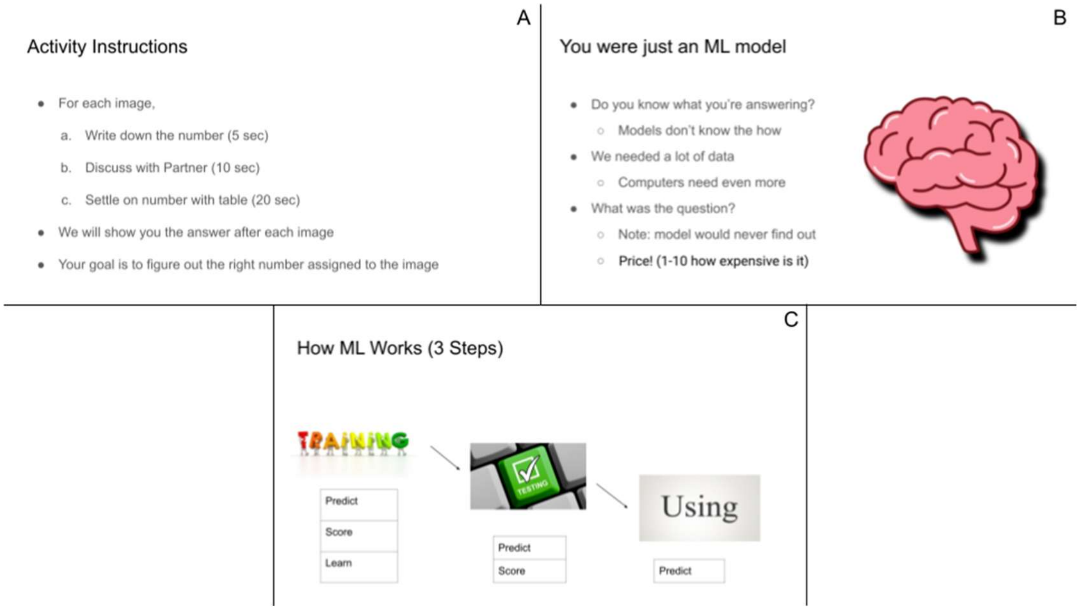

Figure 3: Slides used for activity facilitation. A: The slide presented to students as their instructions for the activity. B: The slide presented at the end of the activity as a guide to the recap discussion that follows the activity. C: The slide used to reinforce the learning outcomes from the activity, highlighting the different stages of Machine Learning and their steps.

2. Example Table for Recording Student Guesses

Table 2 provides a tabular example of the students' guesses alongside the actual object values as they would be recorded on the large class whiteboard and viewed at the end of the activity. Each cell would be incrementally filled out during the respective stage of the activity as the activity progressed. The example presented below (Table 2) is from one instance of running our activity in the classroom.

Table 2: Student-guesses and actual values for the 'worth' object in images shown during each stage of *Becoming an ML Model*. This is an example of what would be on the class whiteboard during the activity. During training, notice that the guesses eventually converge closer to the actual value associated with the

Image Number		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Stage	**Guess/Actual**	**Guess/Actual value for Image #**												
Train	Guess	7	0	3	2	3	1	9	3	1	0	7	1	10
	Actual	1	6	4	7	2	8	10	3	5	1	6	1	10
Test	Guess	1	7	1	4	4	8	Test accuracy: +/-1 away from actual value						
	Actual	2	8	2	3	5	7							
Use	Guess	4	2	8	3	3								

worth of the image.

Appendix B: Activity Considerations and Tips

1. Allowing Student Confusion about Opening Instructions

When given the opening instructions for the activity there will likely be significant confusion and students may ask what exactly they are guessing. This intrigue can help create excitement; it should be fed by responding with something like "you will find out" or other words of encouragement that help build anticipation.

2. Timing each step of *Guess, Discuss, Answer, Learn*

Each of the steps of *Guess, Discuss, Answer, Learn* serves a unique purpose by bringing all opinions and voices into the discussion. The first two steps ensure that those who might be less inclined to share their opinion are given the time and opportunity to create and share their ideas. It also allows instructors to gauge where the class is at and calibrate their guidance and facilitation for the upcoming table group discussion in step 3. It is important that each of the three timed steps are timed through a visible timer and that the next step begins right after the previous one ends. This adds a sense of urgency which is integral to keeping the students engaged while staying within the allotted time.

3. Facilitating Students' Discovery of the Activity Goal

When looking at the images, the number that the students are supposed to be guessing is the response to the prompt: "On a scale from 1-10, what is the worth of the object in the image." For *Becoming an ML Model* to succeed, it is important for the students to figure this out before the end of the training stage. Often, it may become necessary to subtly lead student-guesses towards the end goal; it helps to have a couple activity facilitators present. These facilitators should go around to the tables and provide guiding questions if the table group seems stuck or if we are approaching the end of the training stage. We typically ask the students what they notice in the image, if they can identify anything about objects in the image, or what their hypothesis is and what justifies it. One aspect in your favor is that often when one table figures out the relationship between the image and the number, other tables may overhear this consciously or subconsciously, which will prompt them to guess similarly.

4. End of Activity Discussion Guidance

The facilitator should lead the end-of-activity discussion by asking questions in support of communicating the learning outcomes listed in the discussion portion of the implementation section. Some example questions to steer the discussion in the right direction are as follows:

- When asked questions like this, does an ML model know what it is answering?
- Why did we have to do a training stage?
- What benefit did the testing stage give us?
- Why is a model only useful when making predictions on unlabeled data?
- Did you figure out what the numbers meant? Would an ML model ever truly know?

5. Image Choice Considerations

To make sure students discover the goal, the images used must be carefully chosen. Many students may initially look at the visual makeup of the image itself (i.e. brightness, average color, sharpness), before trying to find patterns between the actual items displayed in the images. Alternatively, students often start counting objects in the image. To steer students towards the correct pattern, we intentionally include images that disprove these other guesses. The image of seven bananas labeled as a "1" (Figure 2) helps disprove the guess that the number refers to the number of items in the image. Images with varying brightness, those with many or few colors, and those containing various shapes and compositions are intentionally included within the image dataset, each with numbers on either side of the spectrum to push students away from these types of guesses. We also include more obvious outliers as the training stage comes to a close, including very cheap and very expensive things with scores of 1 or 2 and 9 or 10 respectively. If you would like to use our images, a copy of the slides used in the activity is linked in Appendix A.1.