EXAMINING PRESERVICE TEACHERS' PROFESSIONAL NOTICING OF STUDENTS' MATHEMATICS THROUGH 360 VIDEO AND MACHINE LEARNING

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Preservice teachers (PSTs) often demonstrate difficulty learning to attend to content-specific student actions in-the-moment. However, machine learning algorithms applied to PSTs' viewing of 360 videos provides a potentially useful tool for teacher educators. In this paper, we describe the initial development of such a tool and the implications for its use.

Keywords: Teacher Noticing; Technology; Preservice Teacher Education.

"Effective teaching requires attending to students' mathematical thinking and reasoning during instruction" (AMTE, 2017, p. 16). These skillsets of attending, interpreting, and responding to students' mathematical reasoning encapsulate *professional teacher noticing* (Jacobs et al., 2010; van Es & Sherin, 2002). When observing mathematics classrooms or viewing video of such contexts, novice teachers often attend to the teacher's actions or describe students' non-mathematical activities, whereas more experienced teachers focus on a specific set of students and describe their mathematics in detail (Huang & Li, 2012; Jacobs et al., 2010). There is clear evidence that, with appropriate scaffolds, preservice teachers (PSTs) can progress to more specific, focused professional noticing (Schack et al., 2013; Teuscher et al., 2017), with mathematics teacher educators continuing to pursue improved techniques and technologies to facilitate such pedagogy. Typically, standard video has been used as the technological medium for facilitating professional noticing in mathematics methods courses (van Es et al., 2017). However, recent technological advances have made certain tools and mediums more commonly available. One such medium is 360 video, which is a version of virtual reality that records video omnidirectionally (see Figure 1). Specifically, PSTs viewing a 360 video can choose which direction to look in the recording, whereas standard videos (e.g., camcorders, Swivl cameras) select what is viewable a priori (Balzaretti et al., 2019; Kosko et al., 2021).

Evidence suggests that 360 video may facilitate PSTs' professional noticing, by creating a viewing context more representative of being in the classroom (Kosko et al., 2021; Roche & Rolland, 2020). Beyond this, 360 video allows for PSTs' choices of *where* they look in a classroom to be measured by recording their selected field of view (FOV). Extending the potential of this technological affordance, recent advances in machine learning, or artificial intelligence (A.I.), allow for examination of patterns in what PSTs focus in their recorded FOV. The purpose of this paper is to examine the efficacy of a machine learning algorithm in identifying the kind of mathematical actions that students engage within a video, and use of such a tool to examine PSTs' professional noticing. This paper reports on our initial efforts to align attending behaviors of PSTs (observed by teacher educators) with patterns recognizable from a machine learning algorithm.

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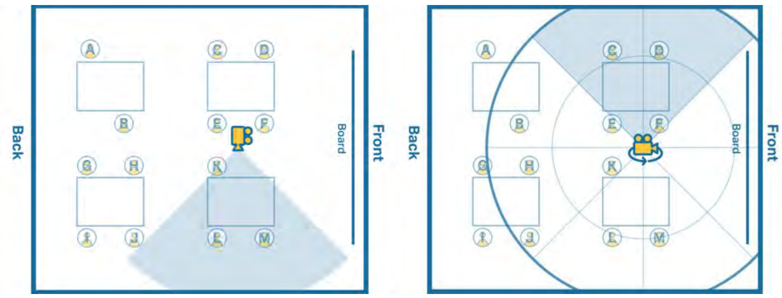

Figure 1: What is viewable from a standard video (left) vs. a 360 video (right).

Background Literature & Theoretical Perspectives

Attending as part of Professional Noticing

Professional noticing involves identifying key aspects in a pedagogical context, interpreting those aspects to one's professional knowledge and norms, and then applying this reasoning to decide how to engage next (van Es & Sherin, 2002). As noted by Scheiner (2016), scholars examining PSTs' act of identifying key aspects have often focused on PSTs' perceptions rather than examining the constructs of attention or awareness. However, "attention selects certain stimuli of a perceived scene for detailed analysis, while perception goes to build up a certain visual experience" (Scheiner, 2016, p. 231). Furthermore, attention involves coordination between various elements of one's professional knowledge and contextual resources. Studies including eye-tracking to examine professional noticing provide insight in how attending is actualized by teachers. Comparing 40 inservice and preservice teachers, van den Bogert (2014) found that more experienced teachers focused their gaze on more students but spent a majority of time attending to a smaller, select set of students in the video examined. By contrast, PSTs scanned the room for larger swaths of time and focused their gaze on relatively few students for any meaningful duration of time. Expanding upon such findings, Dessus et al. (2016) observed that more experienced teachers tend to identify a focal sub-group of students that allows them to attend to more specific, fine-grained events. By contrast, more novice teachers were observed to scan a wider range of events and students, thus limiting their ability to focus on more specific events. Studying this phenomenon using 360 video, Kosko et al. (2021) found that PSTs with less variance in where they attended also had more specific descriptions of children's mathematics. By focusing more attention on two front tables in the classroom, certain PSTs were able to describe more specific aspects of the lesson that occurred. Such findings resemble those of Dessus et al. (2016) and suggest there may be several ways to examine teachers' attending behavior.

As noted by various scholars, professional noticing in general, and attending in particular, are complex skills, but can be taught and learned (Jacobs et al., 2010; Schack et al., 2013). Key commonalities in many of these successful approaches include numerous interactions with videos of students engaging in mathematics, and a focus on giving "opportunities to recognize the power of attending to the subtle details in individual children's strategies" (Jacobs et al., 2010, p. 176). Analysis of such teacher education initiatives have yielded frameworks for specificity of teachers' articulated noticing. As noted by Barnhart and van Es (2015), teachers may initially describe classroom management events and/or focus on the teacher with little focus on students' content-specific actions. As teachers begin to attend to and interpret students' actions, they may describe them from a procedural perspective before eventually learning to describe them from a more conceptual view. Jacobs et al. (2010) provide one example of such

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progression noting that more conceptual-based attending involved specific descriptions of a student's decomposition of numbers by place value and use of benchmark numbers. By contrast, a more procedural attending included descriptions of the numbers the child wrote down and that they added them, but concepts of place-value were absent.

The preceding paragraphs describe how teachers' attending has been examined from data of where and how they look in a recorded scenario and the specificity of how they describe such events in written or spoken noticings. Different scholars have examined the overlap in these sources of data using 360 video (Ferdig & Kosko, 2020; Kosko et al., 2021), wearable cameras (Sherin et al., 2008), and through analysis of teacher discussions while viewing videos (Jacobs et al., 2010; Schack et al., 2013). Each approach has demonstrated capacity for facilitating teachers' professional noticing, but they are often time-intensive and become less practical when considering large cohorts of PSTs in a teacher education program. This limitation motivated the need for applying machine learning to the study of PSTs' attending, with a long-term hope of applying this technology in pragmatic contexts (i.e., mathematics methods courses). Before describing our use of machine learning, however, we provide a brief overview of this technology and our vision for applying it to study professional noticing.

Applying Machine Learning to Study Professional Noticing

Machine learning is an artificial intelligence (A.I.) subdomain that relies on the ability of a machine to learn from an external source and develop and refine its own algorithms and routines toward a given goal. This goal may descriptive (describing a phenomenon), predictive (predicting a phenomenon), or prescriptive (suggesting how a phenomenon should occur). This technology has been used in education in two different ways. First, it has become a STEM field itself to explore and investigate in primary education – particularly high school (e.g., Korkmaz & Correia, 2019; Mariescu-Istodor & Jormanainen, 2019). Second, it has been deployed for staging the so-called "precision education" to develop personalized instruction from individual academic performances (Luan & Tsai, 2021). Recently, there has been increasing attention on machine learning for teacher education, targeting instructional videos. For instance, Goldberg et al. (in press) validated a manual approach for guiding machine learning algorithms in evaluating videos of three university lessons. Specifically, videos of instruction were examined to code for recorded students' visual engagement in class. Nückles (2020) explored eye tracking and related machine learning processes in video professional development for teachers, claiming that more efforts based on computation are needed for understanding how educators deal with lesson recordings and their elements. In particular, Nückles (2020) questioned the relevance of some eye tracking and machine learning approaches to video analysis in teacher education as focusing too much on teachers' perceptions of on/off task student behavior. Instead, there is a need to address how such technologies may be used to facilitate PST education. In line with Nückles (2020) view, we argue that such tools can be used to provide PSTs feedback in how they attend within a classroom, and this feedback can be used to improve their practice. Yet, to reach this eventual application to teacher education, examination and piloting of machine learning must take place. Thus, the purpose of this paper is to examine the efficacy of a machine learning algorithm to examine PSTs' professional noticing.

Method

Participants & Data

Analysis in this paper focused on six PSTs' viewings of a 360 video focusing on 4th graders' solving fraction equivalence tasks (2 minutes, 49 seconds). Data represents a subsample of 70

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PSTs who participated in a larger study. Specifically, the analysis presented here reports on the training process for the machine learning algorithm used to analyze PSTs' 360 video viewing experiences. All six participants were preparing to become elementary teachers in a Midwestern U.S. teacher education program. The program included two focused mathematics methods courses. A focus of the second methods course is fraction pedagogy, including several video-based assignments focused on improving PSTs' professional noticing of students' mathematics (two such videos focus on fractions). Participants included a junior enrolled in their first mathematics methods courses (Nate), three seniors enrolled in their second mathematics methods course (Lynn, Aubrey, & Brie), and two seniors completing student teaching (Anna & Nash).

PSTs participated in the study near the end of their Fall 2020 semester (after Lynn, Aubrey, & Brie had viewed prior videos on students' fractions). As part of a larger study, participants were asked to watch the 360 video focusing on 4th grade students solving a task to determine equivalent fractions. Within the video, students were initially asked to use pattern blocks to find how many red trapezoids covered the shaded region of given shape ($\frac{3}{4}$). Next, they were asked to use green triangles to find the equivalent fraction ($\frac{9}{12}$). Towards the end of the video, student I suggested the answer was $\frac{8}{12}$, to which student G disagreed. Following the teacher's press for student G to "prove it," G demonstrated that there were three triangles for every trapezoid.

Prior to watching the scenario, PSTs were prompted to take notes on any 'pivotal moments' regarding students' mathematics they noticed in the video. Following viewing the scenario, participants were asked to transcribe (type) their notes and then to select one moment to describe as the most important and explain why it was significant. Participants were also prompted to describe what should happen next in the lesson, but the preliminary nature of this analysis, we currently focus on PSTs' attending and interpretations in this paper. In addition to written noticings, participants' viewing sessions of the 360 videos were recorded to allow for analysis of where PSTs' turned their perspective in the 360 video, and what in the scenario they focused on at specific timepoints in the video.

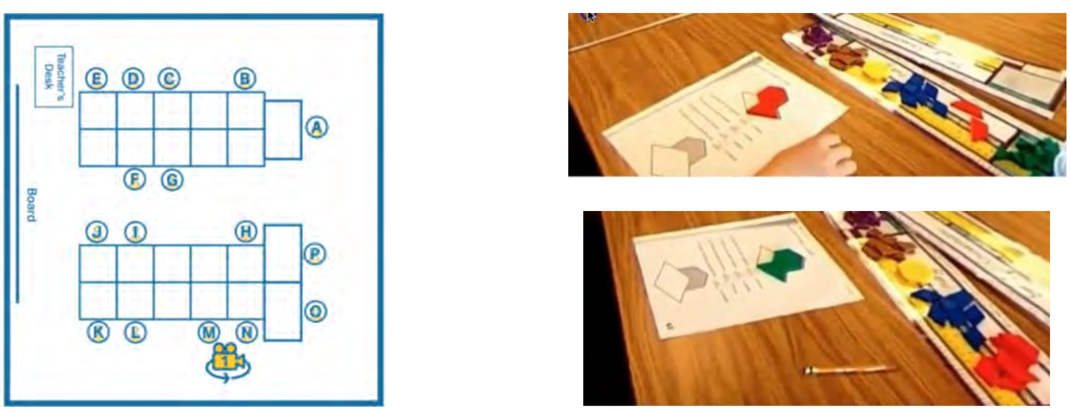

Figure 2: Classroom map with camera positioned between students M & N (left) and screenshots of student M's equivalent fractions (right).

Analysis & Findings

Machine learning in the context of video-based data involves identifying specified visual patterns and teaching the computer-based algorithm how to find the same visual patterns and provide feedback for when the A.I. provides false-positives or false-negatives. To facilitate this

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process in our current work, we incorporated an iterative analytic process. First, participants' screen recordings of their 360 video viewing experiences were collected from the Praxi platform. Next, body tracking was used to overlay digital "skeletons" of recorded students and teacher to identify their torso, orientation of their arms, and direction of where recorded individuals' heads were turned (see Figure 5). The first, third, and fifth authors then analyzed PSTs' screen recordings second-by-second to identify observable student actions present or absent from participants' viewings. Given prior evidence that suggests PSTs' written noticings are related to what and where they attend when watching 360 video (Ferdig & Kosko, 2020; Kosko et al., 2021), PSTs' written noticings were also examined as a way of ensuring that analyzed videos were more likely to include relevant patterns to train the A.I. The analysis and findings of each stage is provided in the sections that follow.

PSTs' written noticings. Analysis of PSTs' written noticing was conducted using Systemic Functional Linguistics (SFL) (Halliday & Matthiessen, 2014, Eggins, 2004). SFL is a methodology for examining how participants' use of grammar conveys meaning. In the present study, we examined PSTs' conveyed meaning through use of reference (i.e., PSTs' use of grammar to refer to grammatical objects). In particular, *reference chains* are formed by the repeated incorporation of references throughout a written text. As a referent continues to be used, the writer may provide additional information, thereby transforming, expanding, or clarifying the meaning of this referent. To analyze for reference chains, and how a referent's meaning was conveyed, the first and third author analyzed written text for PSTs' use of nominal groups and transitive processes. Figure 3 illustrates a snapshot of this process for two students, Nash and Anna. Nominal groups referring to pivotal moments are underlined, where a nominal group "is the part of the clause [that] contains nouns and the words that accompany nouns" (Eggins, 2004, p. 96). Each clause established by the user is separated by "//". Transitive processes, bolded in Figure 3, represents how the participants conveyed meaning for referent nominal groups.

Nash

Some pivotal moments I noticed were from student M and N. //
When the teacher **asked** the questions about
what shapes to **fill** in their diagram and //
find the answer.
Some pivotal moments **were** when the students **were** able to immediately **find** the answer and // were eager to raise their hands.
Also, they quickly noticed the teacher's "error" and //
wanted to address //
and // **fix it** because they **knew** the answer.

Anna

There **were** a few pivotal moments in the video. //
One of the first ones **was** when the teacher has the children define how many green triangles were needed to fill the WHOLE shape. //
The student, I, was **given** the opportunity
to **think** and **respond** to both the questions //
how many to fill the whole and //
how many to fill the shaded. //
It is interesting that this student **responds** with a fraction, 8/12's. //
A key pivotal moment in the middle **is** also when the other students announce they disagree with that answer. //
The teacher **says** there is a debate //
and challenges the student, G, to **prove** it.
G then goes to **show** //
how she **counted** the six in the top part and
then the three in the bottom part
to get 9/12's not 8/12's.

Figure 3: Example of written noticings of Nash and Anna.

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Notable in Figure 3, Nash identifies the pivotal moments in the lesson as focusing on students finding an answer. The referents “what shapes to fill in their diagram” and “find the answer” both point toward this. Further, finding the answer is continuously referenced throughout the text. Towards the end, this manifests in a judgment of “the teacher’s error” and students fixing “it” (the answer) because they knew the correct “answer.” Similar to Nash, analysis of Brie and Aubrey’s reference chains also indicate a focus on students finding the answer. By contrast, Anna’s written noticing (see Figure 3) focuses more on fraction-based references. Initially, Anna references the pivotal moment as children “define how many green triangles…to fill the WHOLE shape.” This referent is clarified by the referents “fill the whole” and “fill the shaded” and then later with students’ responses of “8/12” and “9/12.” More than providing a math-specific referent, Anna’s response differs from Nash (and Brie & Aubrey) by the transitive processes used to convey the referents’ meaning. Nash continuously uses processes like **find**, **fix**, and **knew** “the answer” whereas Anna uses **think**, **respond**, **prove**, **show**, and **counted** to refer to the parts in relation to the whole. So, while Nash, Brie, and Aubrey’s reference chains focused on “the answer,” Anna, Nate and Lynn’s reference chains focused on children’s actions on and with fractions. Referencing Figure 3, We used these findings to help triangulate results of our preliminary video analysis and that of the A.I..

PSTs’ 360 video viewings. Following an analytic approach we have previously used (Kosko et al., 2021), the first, third, and fifth authors examined each participants’ screen recorded viewing second-by-second to identify which recorded students were in their field of view (see Figure 4). We then used findings from analysis of their written noticings to look for differences between PSTs’ viewing patterns. Figure 4 provides one example comparison between Anna, who attended to the mathematics, and Brie, who attended to students’ finding the answers (but no explicit reference to mathematics). Notably, between 44-88 seconds in the video, Anna tends to switch her field of view focusing on student M and students I and J, and these two sets of students are along the same line of sight from the camera perspective (see Figure 4). By contrast, Anna includes students M, J and I, H, and P in her field of view during the same timeframe. Notably, these students are not in the same line of sight but require the viewer to turn the camera perspective as much as 110 degrees from one moment to the next. At around 90 seconds in the video, Anna and Brie’s viewing patterns appear similar. This is when a class discussion begins regarding the task involving a fraction of $\frac{8}{12}$ or $\frac{9}{12}$. Thus, it appeared that any significant differences in viewing patterns were within the first 1.5 minutes of the video.

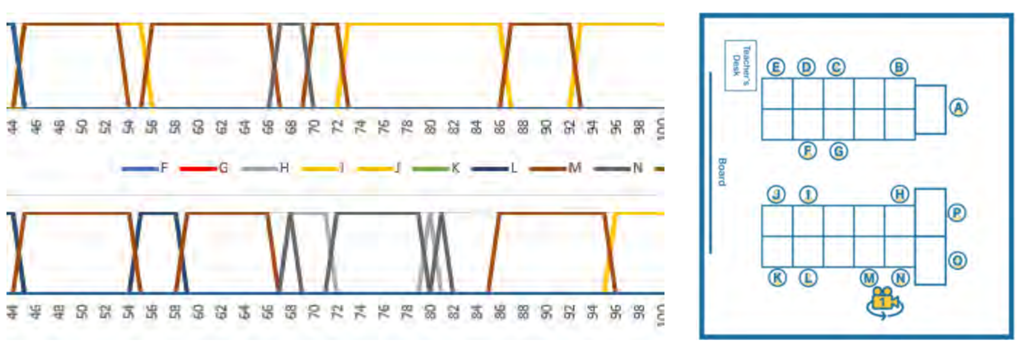

Figure 4: Anna (top) and Brie’s (bottom) student focus.

Next, videos were reexamined using the skeleton wireframes as a guide while focusing on specific intervals identified in the initial video analysis. Specifically, we used AlphaPose (Fang

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et al., 2017; Li et al., 2019; Xiu et al., 2018) to estimate skeleton points of students in the videos, and attached these wireframes to the video, with the goal of using a machine learning approach to analyze them. This allowed for several particular patterns to emerge from the data, but we discuss one such pattern for sake of space and focus. Common in screen recordings of PSTs like Anna was a focus on attending to students' working with the pattern block manipulatives. This was characterized by the skeleton wireframes when students' arms were both pointed inward and their head-gaze was directed downward (where their arms meet). Such instances were present across all screen recordings, but at varying frequencies. Figure 5 provides a comparative example of Nash and Anna's viewing patterns at two instances in the recorded scenario. At 38 seconds, Anna is focusing on student N's manipulation of green triangles onto the figure while Nash is adjusting his field of view from one end of the table to another (back-and-forth). At 50s, both PSTs are attending to student M, but Anna is also attending to students I and J (within the same line of sight). The first and fifth author coded for presence of these skeleton wireframes (K=0.87) and found that Anna attended to students' use of manipulatives for 51 seconds in the first 90 seconds of the video, while Nash did so for 28 seconds in the same interval (no such moments occurred after 90s in the video).

Nash

Anna

Figure 5: PSTs' attending captured, with wireframes overlain, at 38s (left) and 50s (right).

Initial machine learning results. Based on the initial analysis of participants' screen recordings and written noticing, a machine learning algorithm was developed to identify whether participants attended to students' manipulating fractions. We proposed three layers of a neural network model, which has an input layer, a hidden layer, and an output layer. We used categorical cross-entropy loss to update the parameters in the model, and trained the model for 20 epochs to achieve better performance. Developing and teaching a machine learning algorithm takes multiple iterations, and we report only on the initial run of the model. In training the algorithm, 42 skeleton wireframes were extracted from the sample videos and assessed in comparison to examples provided through the human-coded video analysis. To help train the algorithm further, an additional action was included (students raising their hand) to help the A.I. discern one action from another. The algorithm reached an accuracy of 75.86% in an initial training run (n=29) and then 69.23% on a test run (n=13) of the A.I. Results of the initial training and test run are positive and encouraging, but do call for the need for additional attending

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elements be included, and additional data be collected from participants' videos. Fortunately, our current dataset includes additional 360 video screen recordings of 70 PSTs, and there are several other attending elements (e.g., teacher within FOV, student(s) counting blocks on paper) that will be used to train the machine learning algorithm further. As additional attending elements are included, and more examples are extracted from participants' videos, the A.I. will improve in accuracy and provide a report comparable to human coders (but in a fraction of the time).

Discussion

Similar to prior findings examining more and less sophisticated noticing (Barnhart & van Es, 2015; Jacobs et al., 2010), we found that certain PSTs referenced children's mathematics-specific actions (Anna, Lynn, & Nate). By contrast, others focused on more general (not mathematics-specific) events. Nash, Brie, and Aubrey each attended to how and whether people in the recording found the correct answer. Interestingly, this focus on "the answer" infrequently referred to a numeric fraction. Corresponding to research on eye-tracking (Cortina et al., 2015; Dessus et al., 2016), analysis of PSTs' 360 viewing indicated participants with more sophisticated noticing (via writing) had more focused attention than their counterparts. For example, Anna's focus on three students within the same line of sight contrasted Brie's shifting from one length of the table to the other, and back (see Figure 4). This corresponds to Dessus et al.'s (2016) observation that more experienced teachers focused on subsets of students and examined more specifics, but more novice teachers scanned the room more frequently. However, findings here do not compare expert and novice teachers, but PSTs at similar levels of experience. Thus, findings presented here suggest that PSTs' embodied attending behavior may be due less to level of experience and more to some underlying professionalized knowledge.

This paper includes a diverse set of authors spanning mathematics education, computer science, and educational technology, with each area of expertise represented in the development and application of this new tool for teacher education. Thus, beyond the implications for our specific machine learning A.I., an additional implication is the benefit and need for cross-disciplinary collaboration. As mathematics educators seek to incorporate more 21st century technologies into teaching and teacher education, there is a critical need for such collaboration. This paper serves as an example of what such collaborative efforts can yield, as well as providing a description of how one such technology (machine learning) is developed in such contexts. Specifically, applied machine learning to PSTs' attending in 360 video. Findings are preliminary, but suggest that nuanced student actions relevant to pedagogical content-specific noticings can be detected by A.I. This is highly significant, since prior applications of machine learning have focused on more generic student behaviors (Luan & Tsi, 2021; Nückles, 2020). As the accuracy and breadth of our machine learning A.I. improves, it has potential not only for improving capacity for research of PSTs' professional noticing, but in providing timely feedback for PSTs in mathematics methods courses. Some of the attending element patterns detected with the A.I. described here can be applied to other videos (360 or standard), but such application is likely context specific and require additional training of the A.I. However, such additional validation of these machine learning algorithms will likely yield more robust tools for mathematics teacher educators and teacher education researchers.

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