Supporting Instructor Reflection on Employed Teaching Techniques via Multimodal Instructor Analytics

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Abstract—This work-in-progress in the Innovative Practice Category describes the use of multimodal data capture to inform instructors’ awareness of their activities in the classroom. Broadly construed, learning analytics is the collection and analysis of data in an educational context with the aim of improving educational outcomes. To capture a more wholistic characterization of an educational context, there has been increased interest in multimodal data such audio, gestures, positioning and movement. These data can characterize the content delivered and teaching techniques employed by the instructor. Instructor reflection on both may lead to improvements in instruction.

Presented here is IATracer, a lightweight system for multimodal instructor data capture consisting of a lavalier microphone paired with a positioning badge. The microphone captures classroom audio and using Google Cloud’s Speech-to-Text API with diarization, the instructor's speech can be isolated and transcribed. Analysis of this text can provide insights into what topics were covered, for how long and what questions were asked. Additional analysis could provide the instructor feedback on the delivery (e.g., long monologues) and the level of student interaction (e.g., dialogue, questions directed towards students). Novel aspects of this work-in-progress include the lightweight, economical nature of the system and its use of Google Cloud services. The insights generated by the system will enable faculty to reflect upon their employed teaching techniques and the content of their interaction with students. Such reflection ensures alignment of employed technique with intent.

Keywords—learning analytics, multimodal learning analytics, instructor analytics, instructor monitoring, critically reflective teaching

I. INTRODUCTION

Learning analytics has been defined by the Society for Learning Analytics Research (SoLAR) as the “measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” [1]. As with applications of analytics in other domains, the overall aim is to collect and use data to inform the decision-making process and lead to improvements. These data-driven insights are particularly valuable as they sometimes work against our intuition, offering novel insights and open new directions for improvement.

Given the ubiquity of learning management systems (LMS) in higher education, such systems have proven to be a ready and informative source of educational data. Analysis of LMS data has led to many tools that support decision making for students and educators alike [2]–[4]. In an effort to better characterize the complete learning environment, there has been a push in recent years to go beyond what can be easily captured by a LMS. Additional sources of learning data have included eye-tracking, EEG, accelerometer, location, audio and video [5]. Collectively these data are referred to as multimodal data and their capture and subsequent analysis are known as multimodal learning analytics (MMLA). Specifically, MMLA has been defined as a "subfield of learning analytics (that) focuses on the interpretation of the multimodal interactions that occurs in learning environments, both digital and physical" [6]. Examples of MMLA include monitoring individual learners in the classroom [7], tracking instructor movements [8], predicting teaching actions [5], and analyzing small group interactions [9].

Concomitant with increases in the use of learning analytics have been concerns regarding the ethical use of student data and student privacy. Consider that some institutions now track students’ physical presence through their mobile devices [10]. Privacy (i.e., "the regulation of how personal digital information is being observed by the self or distributed to other observers" [11]) is a concern that has been expressed by students [12]. Care must be taken to ensure that students are seen as agents in the process, providing informed consent to share their data, and not merely seen as sources of data. This concern can partially be addressed by being transparent with data collection, clearly transmitting the aims of data collection and providing students the ability to opt-out. Still, students must be willing to share their data. Once the data is provided, it is imperative that the data is used ethically. This means that methods developed from the data are fair, accurate and do not harm the student. A number of faults and biases have been exposed in recent uses of machine learning [13]. Given the temporal nature of student success and inherent variability in the input (e.g., individual actions or sentiments that can change and individuals can behave in irrational ways), it is very challenging to predict student outcomes such as a final grade or risk factor. By sharing biased or incorrect predictions
with students, such predictions could turn into self-fulfilling prophecies. Comparative learning analytics (e.g., showing a student’s grade in relation to the overall grade distribution) could lead to anxiety. In short, there are still many open questions about the impact of learning analytics on students. Given the current challenges and climate surrounding learning analytics, institutions may be hesitant to move forward.

While the issues regarding the privacy and capture of student data are being resolved, one tractable means of advancing the use of learning analytics is through instructor analytics. With instructor analytics, the gaze of data collection turns towards the instructor. This largely sidesteps the difficulties of working with student data. Additionally, the instructor typically already has the authority needed to capture the data and can do so without the need for large scale, institutional buy-in. While smaller in focus, instructor analytics still provides data on the learning environment and through analysis and critical reflection on the part of the instructor, improvements can be made for the benefit of the student.

II. BACKGROUND

Several systems have been developed to capture and characterize what goes on in the classroom. Martinez-Maldonado et al. created a system that generated teacher notifications for group collaborative tasks [14]. In the study, small groups used interactive tabletops that monitored progress and sent the instructor real-time notifications of events such as misconceptions or slow group. In the context of training simulations in health care, Echeverria et al. used localization sensors, physiological wristbands and microphones to create a multimodal matrix describing physical, social, epistemic and affective aspects of group activity [9]. Dimensions of the matrix were extracted and analyzed post hoc to describe colocated social interaction and electrodermal activity. Prieto et al. evaluated a set of sensors (e.g., eye tracker, accelerometer, microphone) worn by the instructor to automatically categorize the instructor’s activity (e.g., explanation, monitoring) [5].

Making improvements in teaching practice is a formative process. An instructor creates an instructional plan to help students attain specific educational outcomes, implements the plan, collects feedback and uses the feedback to inform the creation of future plans. In devising such plans, an instructor bases his or her actions on assumptions about how to effectively help students learn. Critically reflective teaching is “the sustained and intentional process of identifying and checking the accuracy and validity of our teaching assumptions” [15]. Important in this reflective process is the validity of the instructor’s perception of what happened in the classroom. As an example, consider the work by Ramsey, Guo and Pursel using flashbacks and recaptures in flexible classrooms [16]. A flashback asked instructors to think back on how they used the affordances of a flexible classroom to explore course content and a recapture summarized how the classroom configuration affected their instruction. This is a reflective process but one that is based on an instructor’s perception of what happened. Instructor analytics and multimodal data capture support critically reflective teaching through an additional stream of unbiased information about where the instructor was and what was said. This ensures alignment between what the instructor thought happened and what really did happen.

Much of the prior work regarding multimodal data capture in the classroom has focused on providing the instructor with actionable information about the student (e.g., dashboards to monitor student progress, event driven notifications). To date, little has been done to provide the instructor with actionable information on his or her teaching practice [5]. Presented here is a multimodal system to capture instructor movement and voice to inform reflection on teaching practice. The system has been termed IATracer, as it provides a trace of the instructor’s position and speech during a class period. A notable difference between IATracer and those previously described is that IATracer system is much less intrusive, requiring fewer sensors.

III. IMPLEMENTATION

The system developed for this work-in-progress was built around the Pozyx creator development kit and a battery powered Raspberry Pi 3. The Pozyx kit included four anchor points and a positioning tag that records real-time positioning with accuracies in the range of 10 to 30 cm [17]. These components were selected due to their price, portability and performance. The Raspberry Pi is an inexpensive, general purpose computing platform that can be battery powered and its size and weight allow it to be carried by an instructor. The Pozyx position system uses an ultra wideband technology that is capable of reliably locate the position of an instructor in the confines of a classroom. Other positioning technologies have much larger accuracies (e.g., >1 m) [17].

The positioning tag connects to the Raspberry Pi via a micro USB cable. The Raspberry Pi is also equipped with a 3.5 inch LCD touchscreen and a lavalier microphone. Together, the Raspberry Pi and Pozyx positioning tag form the instructor multimodal data capture device. The position tag is shown in Figure 1. In addition to the positioning tag, the Pozyx developer system requires four powered, anchor points. These are affixed to the walls of the classroom and each is powered through an AC adapter.

The instructor multimodal data capture device is controlled through the LCD touchscreen on the Raspberry Pi. The Raspberry Pi is driven by a standard Rasbian image that starts a lightweight, local webserver to host the user interface. The web-based user interface is written using the Bottle framework and HTML5. With the interface, the instructor can start and stop audio recordings, manage recordings, submit recordings for transcription and submit positioning information. Network connectivity is achieved through the built-in WiFi on the Raspberry Pi. Figure 2 shows the Raspberry Pi, microphone and a view from the user interface. The Pozyx enclosure is affixed to the back of the Raspberry Pi with a hook-and-loop fastener.

Audio data is transcribed using Google’s Speech-to-Text API with diarization. The diarization identifies and tags voices.
in the audio and the resulting text can easily be filtered to isolate the instructor’s text (i.e., as the instructor wears the microphone, most of the audio should correspond to the instructor and this would correlate to the most frequent voice tag). The Speech-to-Text API is accessed through a simple web application that provides transcripts in portable document format (PDF). Note that Google’s Speech-to-Text API is part of the Google Cloud AI and Machine Learning suite of products and is a pay per use service. At the time of writing, it would cost approximately 1 USD to transcribe 60 minutes of audio.

IV. DISCUSSION

The principle aim of the system is to provide instructors with an additional stream of data to use in the critical reflection on their instruction. By reading the transcript of a class period, an instructor can think back and consider what worked well, what might need to be reworked and why. During this reflection process, the instructor might annotate the transcript and make notes for the next time that material will be presented. Alternatively, annotations and reflections could be spoken and made in real time by the instructor during the class period. As such, these annotations would be automatically embedded into the transcript. A value of IATracer is that its regular use will capture and characterize much more than could be captured through reflections in a physical notebook and the electronic documents generated are much easier to browse than an audio recording.

A. Comparisons with Existing Technology

As mentioned, the aim of IATracer is to inform instructor self-reflection. Other systems, such as Swivl [18], are geared for coaching or monitoring teaching. Nevertheless, instructors could use Swivl to engage in critical reflection of their teaching practices. A notable difference between IATracer and Swivl is that Swivl has a much larger footprint, with video capture and optionally classwide audio capture. The scope of data capture with IATracer was purposefully designed to be narrow so as to limit students’ privacy concerns. Additionally, IATracer is able to track and record an instructor’s position in the classroom over the course of a class period.

The cost of constructing the IATracer system described in this manuscript was approximately 878 USD. This cost includes 30 USD for the the Raspberry Pi 3, 25 USD for the Anker PowerCore ultra compact battery pack, 20 USD for the USB omni-directional microphone, 28 USD for the 3.5 inch Touch Screen with Case, and approximately 775 USD for the Pozxy Creator Kit Lite. By forgoing the tracking capability, the cost of the instructor data capture device would be around 100 USD.

B. Mitigating Privacy Concerns of Multimodal Student Data

IATracer addresses privacy concerns of student data by effectively removing student data from most audio capture and subsequent analysis. If it were possible to transcribe audio locally (i.e., without the need of a cloud-based service), then self-contained student data capture devices could be developed. Such a device could be used, for example, to capture audio of student groups and provide a transcript of their discussion. The transcript could be analyzed to characterize the level of participation by each student or identify questions that members of a group are posing. If enabled by students, real-time analysis of group discussion could identify struggling groups and notify the instructor, similar to MTFeedback, work by Martinez-Maldonado et al. [14].

Self-contained devices would address student privacy and data control concerns in two ways. First, it would put students in control of their data. They could transcribe their audio and then choose to share the transcript, or any analysis performed on the transcript. This approach would be similar to the multimodal selfie, a personal multimodal recording device that is owned and operated by the student, and gives agency over what data is collected [7]. Second, the data would not need to be sent to a remote location for processing. Data would remain local to the device and fully under student control.
C. Implications for Practice

IATracer’s impact on teaching practice is primarily through self-reflection on what an instructor has said and his or her movements in the classroom. With regular use, an instructor has an electronic record of what he or she has said during the course. The transcripts of instructor monologue provide a browsable document that can be consulted. Additional analyses of the transcripts pull out questions asked and topics covered. The practice of in situ critical reflection (i.e., making audible pedagogical comments so that they are later transcribed) could engender a more responsive teaching style, one in which the instructor considers what is happening in the classroom and makes immediate changes. Additionally, some of the artifacts generated by IATracer (e.g., redacted transcripts, questions asked, topics covered) could be provided to students as study aids.

V. Future Work

A. Possible Extensions of the IATracer System

Several extensions of the system are possible that could further inform instructor reflection. Semantic analysis of transcripts from captured instructor audio could be used to reflect on the alignment between delivered content and instructor aims. Segmenting the transcript and applying standard text processing techniques such as topic modelling could identify topic coverage and relative emphasis. If the instructor adopts the habit of repeating students’ questions, a habit that would aid in more complete transcripts since student audio is not transcribed, then common questions or misconceptions could also be tagged and extracted. Given the technical nature of the discourse in engineering disciplines, standard topic modeling applications may struggle. Since the audio transcribed is only that of the instructor, the identification of questions is straightforward, keying in on the use of interrogatives. Additionally, the instructor could speak a key phrase (e.g., “the question is”) to ease identification of relevant questions. Automatic identification of answers to students’ questions embedded in the transcribed instructor monologue would be more challenging. Still, an instructor could use key phrases to bookend answers and enable easy extraction.

Another extension of the system that would further instructor reflection and characterize the centrity of the employed pedagogy is through analysis of the raw audio recordings. The recordings of the instructor could be analyzed using non-semantic machine learning techniques such as those used by Owens et al., to assess the degree to which a class period uses active learning [19]. Note that the intent of these analyses would not necessarily be to further adoption of active learning or student-centered pedagogies but rather to help instructors reflect the alignment of their intended pedagogy with that which is employed.

B. Possible Applications of the IATracer System

An additional application would be to couple the system with flexible classrooms and research on classroom design. Ramsay et al. studied instructor use of a learning space through regular “flashbacks” (i.e., a weekly written reflection on how the affordances of a flexible classroom were used to explore or interact with course content) [16]. The fidelity of Ramsay’s approach could be enhanced by fitting furniture in a flexible classroom with positioning tags to monitor how the furniture is arranged during class periods. This data could be presented to the instructor later, along with prompts to help the instructor think about his or her pedagogical aims and how they aligned with the configuration of the space. This positioning data would also help characterize the degree to which an instructor uses teacher-centered versus student-centered pedagogies (e.g., arrangements of student seating in rows would be indicative of teacher-centered instruction while group seating would be indicative of peer instruction).

VI. Conclusion

This work-in-progress has presented a multimodal data capture device to perform instructor analytics. The device consists of a lavalier microphone paired with a positioning badge. Captured instructor audio is transcribed using Google Cloud’s Speech-to-Text API and provide insights into what was said and what questions were asked. Collectively, these streams of data inform instructors of their activities in the classroom and support critical reflection of their instructional practices. In the context of learning analytics, these insights can help faculty reflect upon their employed teaching techniques and the content of their interaction with students. Such reflection ensures alignment of employed technique with intent and may lead to improvements made for the benefit of the student.

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REFERENCES


