Student Engagement Profiling Using Automated Sensing and Unsupervised Clustering

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Abstract

In light of the evolving educational landscape, our project seeks to leverage advanced facial recognition and gaze tracking technologies to analyze and enhance student engagement in real-time [1–3]. Building on preliminary findings from the previous semester's investigation into teaching styles and student interactions, this research aims to delve deeper into the nuanced dynamics of student attention in classroom settings. By employing sophisticated machine learning models in conjunction with Edulyze's cutting-edge gaze tracking capabilities [4, 5], we propose a second-by-second analysis of student gaze patterns to uncover subtle indicators of engagement. This project not only promises to shed light on the intricate relationship between teaching methodologies and student attentiveness but also aims to equip educators with actionable insights to foster a more engaging and effective learning environment.

Introduction

Our previous work revealed a good performance in predicting classroom activity (COPUS [6], 1) using automated sensing output, including, but not limited to, student gaze movement in 3D. To further expand on the how students' gaze reflect their learning outcome, we decided to identify motifs of students gaze and to explore the possibility of using this as the proxy for student engagement. Specifically, our research will focus on the second-by-second correlation of gaze data with student engagement. The data will be provided by Edulyze [4], and this approach will allow us to capture subtle shifts in attention that may occur throughout a class session. By analyzing video data from 05391A course throughout a semester in 2019, we will reveal the amount of student engagement second-by-second. Moreover, we seek to explain the features that comprises each engagement mode, detailing the whole-body dynamics in a drop in attentiveness.

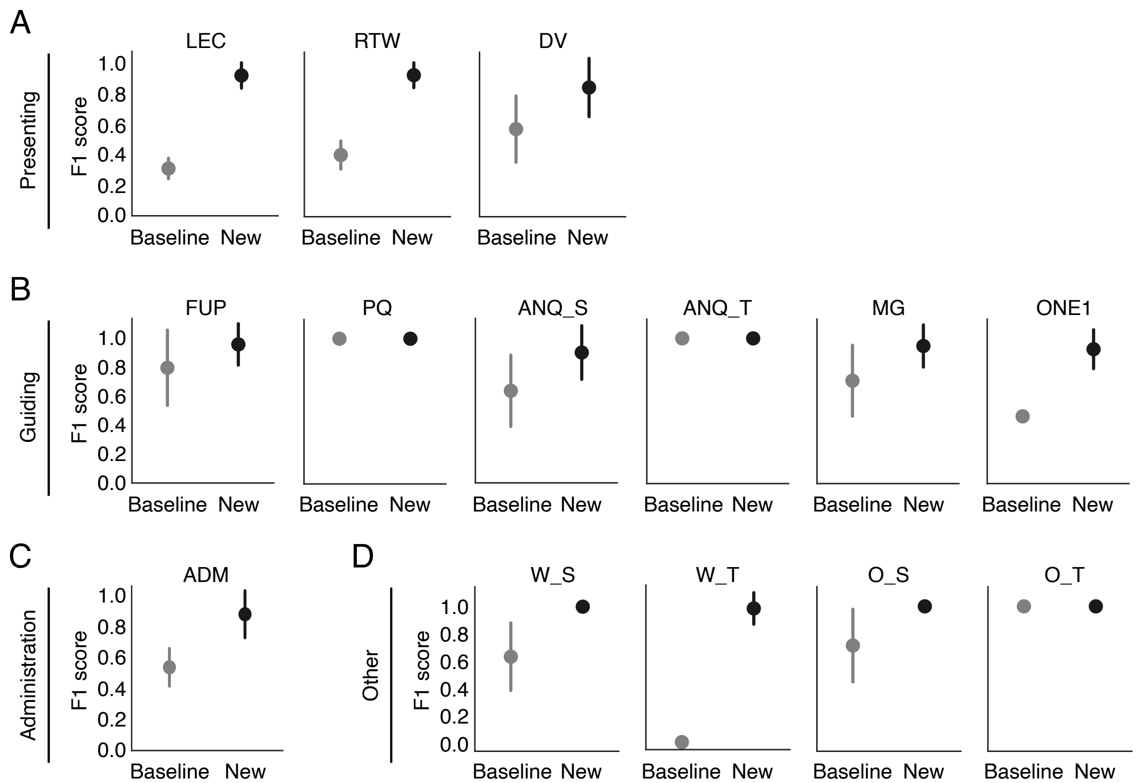

Figure 1: Automated sensing correctly predicting student activity. Mean ± standard deviation of performance on 20 randomly partitioned held-out new classroom data for each of the four main categories (A: Presenting; B: Guiding; C: Administration; D: Other). New is after incorporating 5 sessions from the new classroom - 407, whereas baseline is before. Note that the description of these shorthanded activity can be found in Smith et al. [6]

Methodology

To systematically investigate the correlation between student gaze patterns and engagement levels, we will first utilize DeepFace to preprocess data from duplicating student counts, as well as identifying students across classes. Then, we will identify modes of student engagement using clustering algorithms on multi-dimensional features such as gaze and body movement. Lastly, we will explore the contribution from each feature that delineates across motifs.

Data acquisition and preprocessing

Revisit raw video data from the 05391A course in 2019 and preprocess to remove artifacts of students leaving and re-entering the classroom. To prevent student identities were not duplicated, we will apply DeepFace on student ID tracking throughout the video as well as across videos, by using first few frames from first session as references. This methodology will ideally remove double-counting identities when performing post-hoc or real-time student engagement profiling.

Analytical framework

Deploy clustering algorithms, the likes of K-means, DBSCAN, etc, to dissect and interpret the attention data. Since we do not possess student attention annotations (could be subjective without interviewing the students), we believe a composite features that are associated with gaze and posture would reveal a few modes of student engagement.

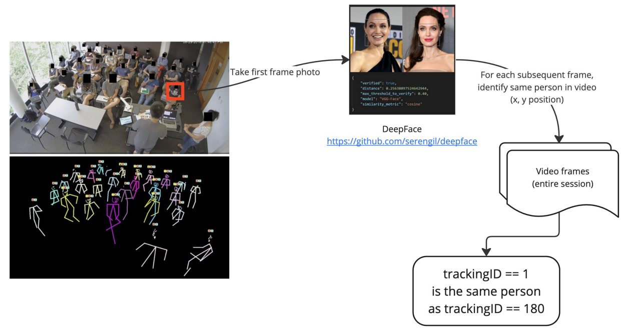

Figure 2: Apply DeepFace to track student iD

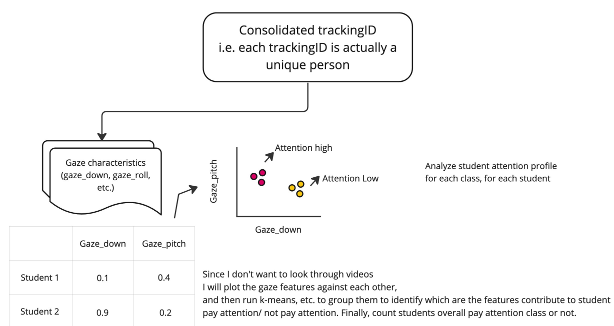

Figure 3: Find correlation between gaze movements

Feature explanation of engagement modes

To further explain the importance of each feature that are the best descriptors of each engagement motif, our approach would be to build a Random Forest Classifier and post-hoc identify the weights for each feature that best predict each type of student engagement mode.

Expected outcomes

Overall, we are trying to identify gaze and whole-body movements that best describe student engagement. We aim to unveil nuanced insights into how students' attention fluctuates during classroom interactions. By clustering the features, we expect to find a few types of engagement motifs across all sessions. If we do, this approach will empower educators to identify student's attentiveness in real-time to potentially enhance their audience's attentiveness.

Discussion

Our research aims to bridge the gap between technological advancements and educational methodologies by harnessing the power of facial recognition and gaze tracking to analyze student engagement. Although we explore the student's engagement pattern via automated sensing post-hoc, we will also shed light into the descriptors that best predict each engagement motif using a classifier design. Overall, we aspire to contribute to the broader goal of enhancing academic success and have instructors dynamically react to real-time reduction in audience's engagement levels.

Proposed timeline

February deliverables: We will finished tracking each student not only throughout a class, but also throughout the entire course. March deliverables: Perform cluster analyses, provide innovative visuals to showcase the various modes of student engagement. Receive feedback from group. April deliverables: Perform detailed analyses on how each feature contribute to each cluster. Receive feedback from group. May deliverables: Finalize the comprehensive report detailing our research findings, conclusions, and recommendations for future applications.

References

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