Engaging or Zoning Out in Class: Automated engagement assessment with unsupervised clustering

Lucia Fang, Prasoon Patidar, John Zimmerman, Yuvraj Agarwal, Amy Ogan

Carnegie Mellon University

Background

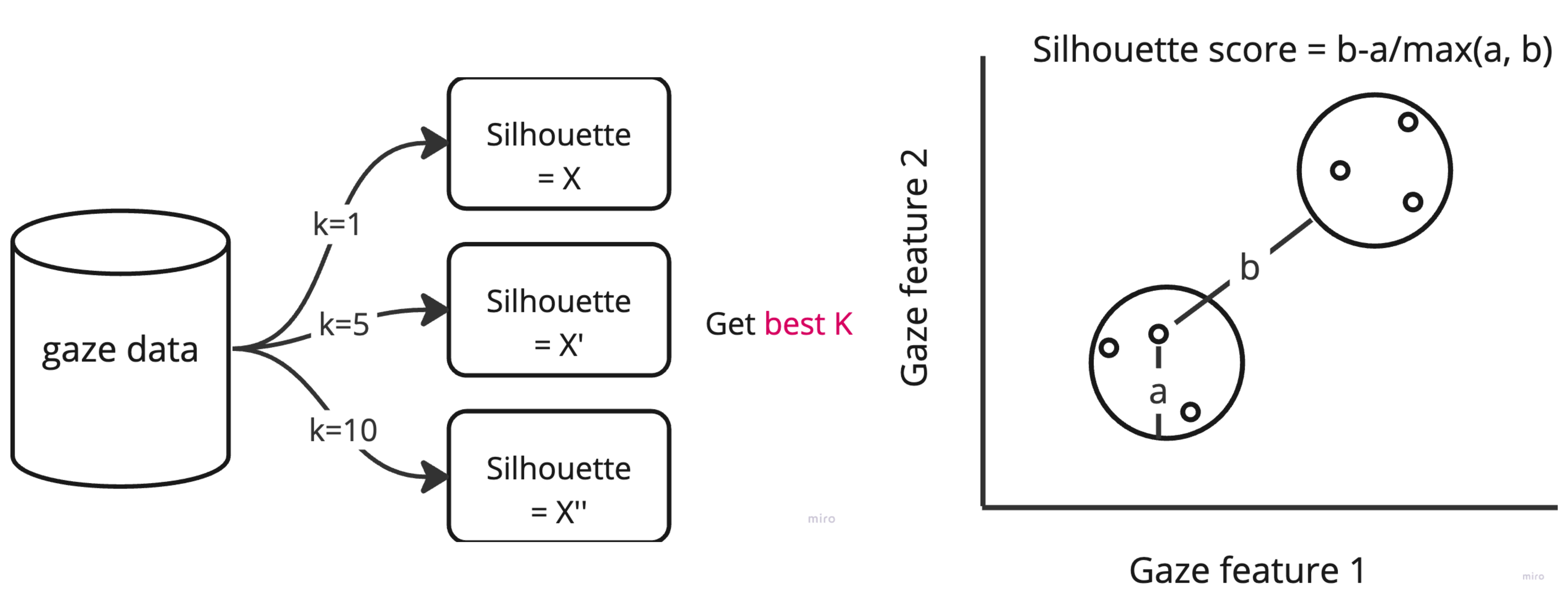
With the recent development of automated classroom analytics using machine learning - Edusense [1, 3], there is still little evidence on the impact of how this type of education technology can be useful to improve personalized learning. Our previous work revealed a good performance in predicting classroom activity (COPUS [2]) 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. 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 [1, 3], we propose an analysis of student gaze patterns to uncover subtle indicators of engagement. By analyzing video data from 05391A course throughout a semester in 2019, we will reveal the amount of student engagement within and across sessions. Moreover, we seek to explain the features that comprises each engagement mode, detailing the composite gaze dynamics in attentiveness.

Research Questions

1. How do students' different gaze directions show whether they pay attention in class?
2. How does time impact students' attention within a class and from week to week?

Methods

To reliably identify the modes of students' engagement, we deployed K-means clustering on all gaze features. Silhouette scores will be used to determine the best number of clusters.



To define the clusters, we analyze the feature distribution. Furthermore, we examine the reproducibility of clustering with the use of RF classifier.

To identify distracted students, we compared students gaze cluster against its 5 immediate neighbors. If and only if none of its neighbors carry the same cluster, it will be marked as an distracted student.

Lastly, to explore the factors that associate with students attention, we plotted students' attention (mean and CI) against time within a session and time across sessions.

Results

Unsupervised clustering of student gazes

Fig. 1 Euclidean distance (red) and Silhouette score (blue) for various K-means clusters

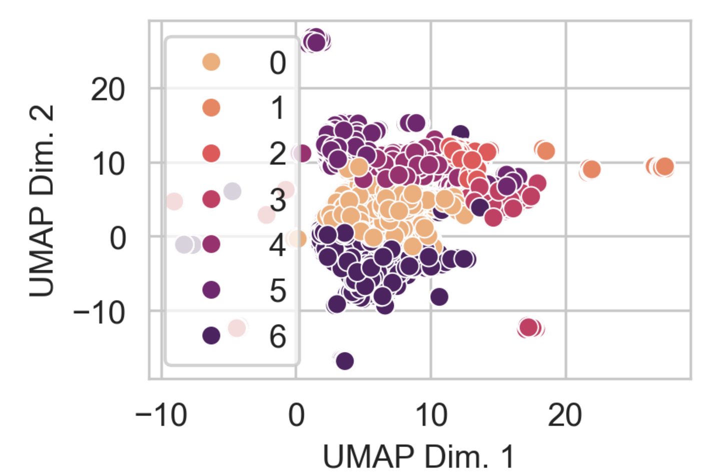


Fig. 2 Two dimensional representation of gaze features colored by K-means clusters

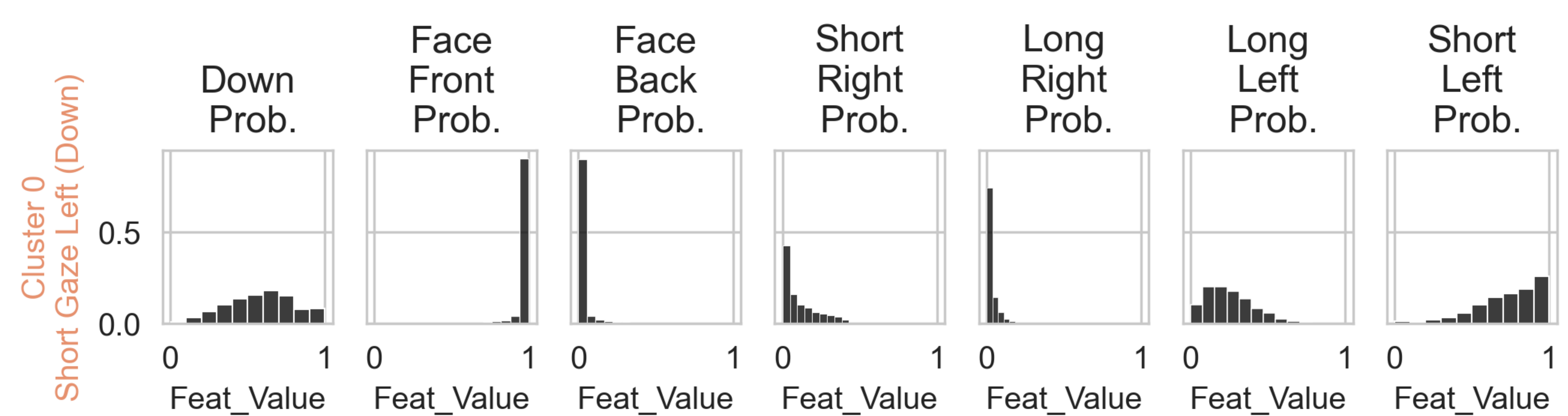


Fig. 3 Feature distribution for example cluster identified through K-means.

Using classifier to reproduce clustering

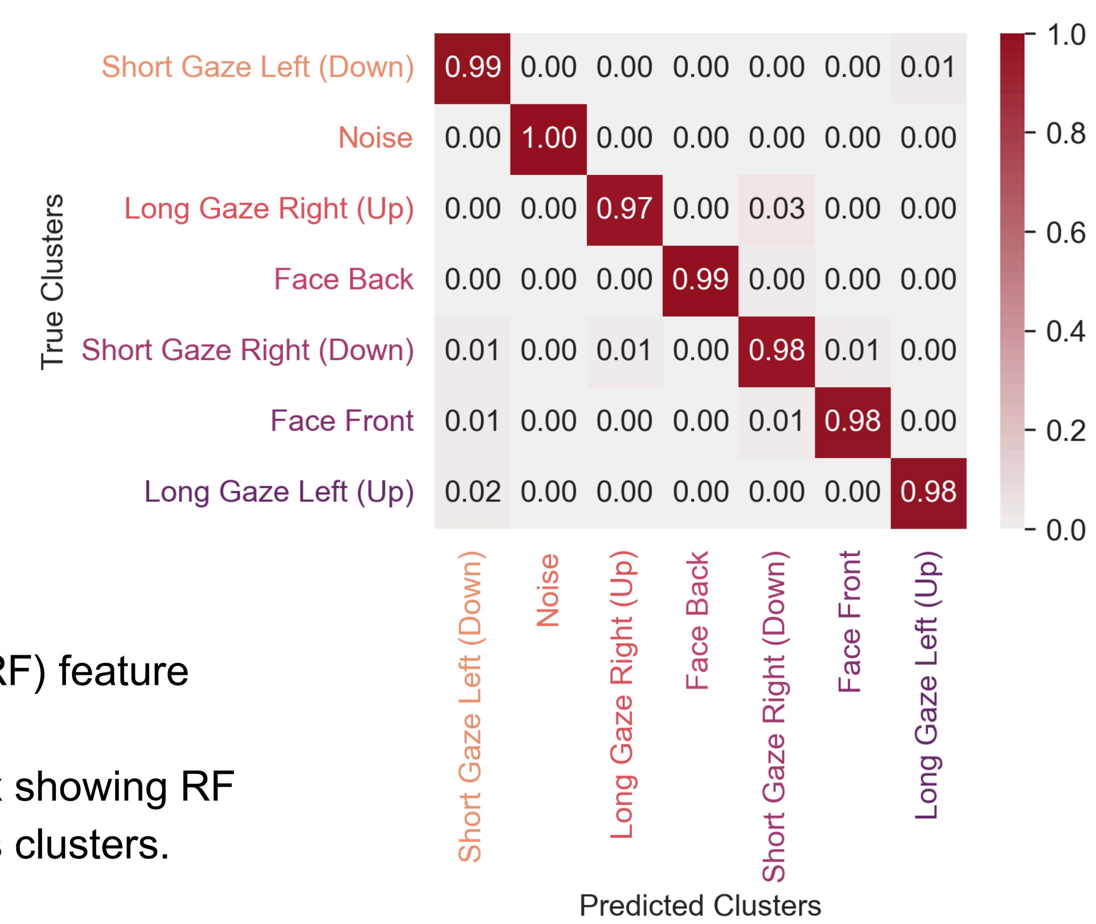


Fig. 4 (Top) Random Forest (RF) feature importance

Fig. 5 (Right) Confusion matrix showing RF predicted clusters vs. K-means clusters.

Schematic for identifying outliers

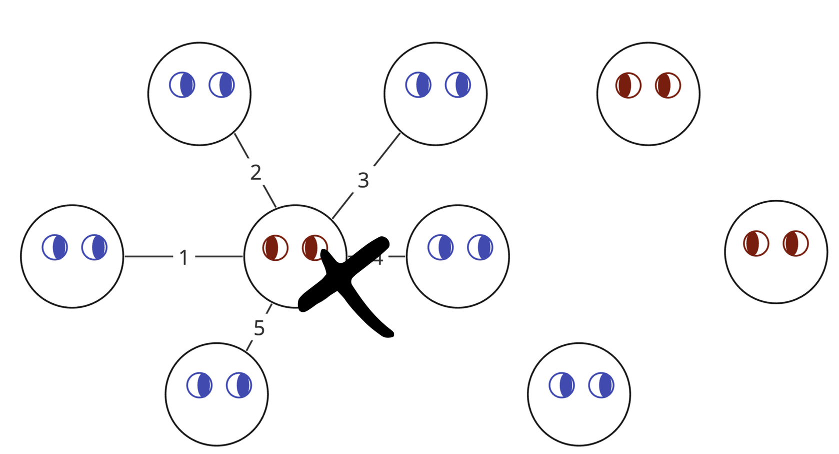


Fig. 6 (Left) The leftmost red is considered as an outlier because the five closet neighbors are all looking towards the opposite direction.

Use outliers to calculate mean students' attention

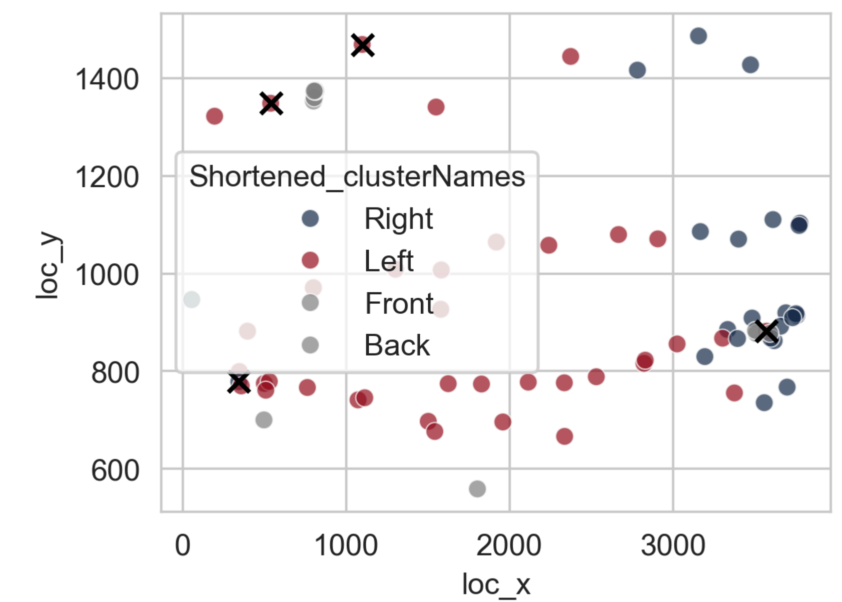


Fig. 7 Location scatterplot at 2-4 mins mark of an example session colored by cluster; 'X' marks outliers

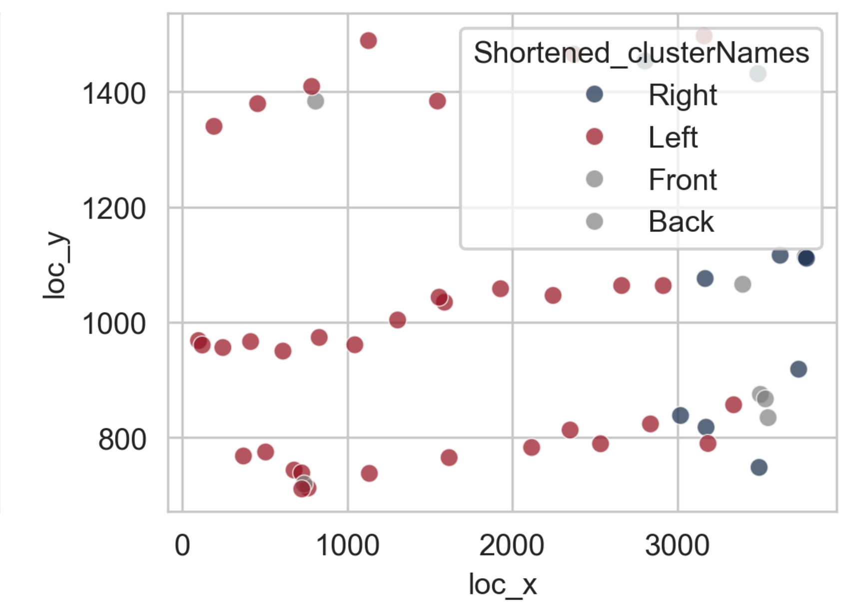


Fig. 8 Location scatterplot at 4-6 mins mark of an example session colored by cluster; No 'X' present

Identify factors that reduce students attention

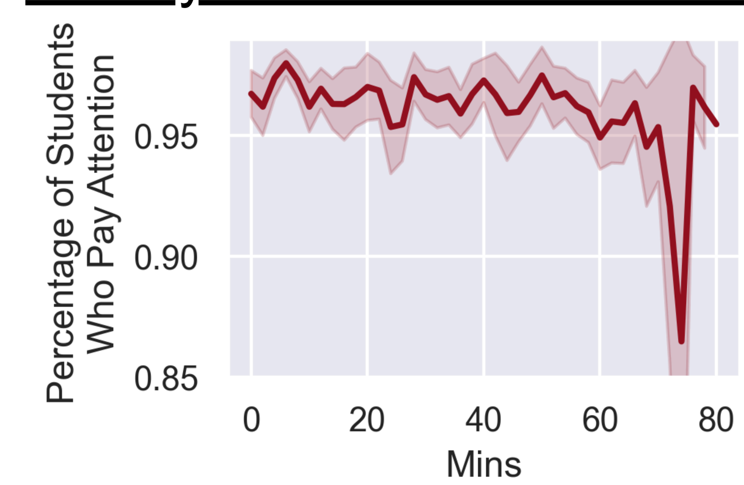


Fig. 9 Percentage of students who pay attention (mean with CI) over an 80 mins session in 05391A

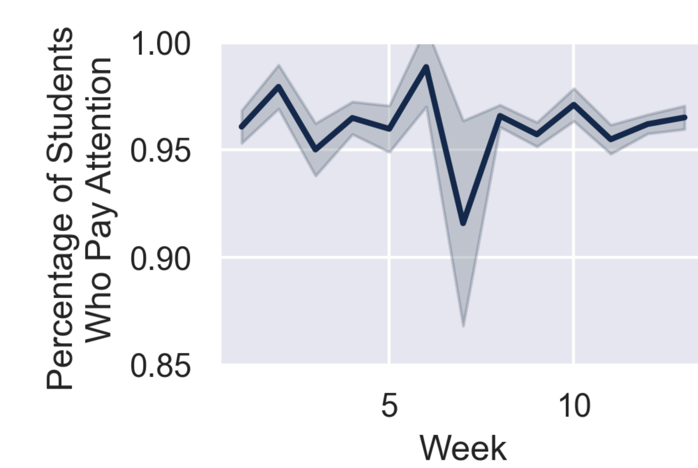


Fig. 10 Weekly percentage of students who pay attention (mean with CI) in 05391A

Conclusion

1. Using unsupervised clustering, we have identified 7 modes of students gaze. Distracted students are identified by opposing gaze modes to the nearest five.
2. Students' attention appears to reduce after overtime in an 80 mins session. However, there does not seem a decrease overtime across sessions, though there is a sharp drop in the middle of the semester.

Limitations

1. Although 5 closest is sufficient in current setup, the parameter will be need to adjust depending on class size.
2. In our case, there is only one instance where all 5 closest are outliers. Therefore, this particular scenario needs to be addressed.

References

1. Ahuja, K. et al. EduSense: Practical Classroom Sensing at Scale. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol 3, 71. https://doi.org/10.1145/3351229 (2019).
2. Smith, M. K., Jones, F. H., Gilbert, S. L. & Wieman, C. E. The classroom observation protocol for undergraduate stem (COPUS): A new instrument to characterize university STEM classroom practices. CBE Life Sciences Education 12, 618–627. issn: 19317913. https://www.lifescied.org/doi/10. 1187/cbe.13-08-0154 (Dec. 2013).
3. Ngoon, T. J. et al. "An Instructor is [already] able to keep track of 30 students": Students' Perceptions of Smart Classrooms for Improving Teaching & Their Emergent Understandings of Teaching and Learning, 1277–1292 (July 2023).