EduVida: Exploratory sensing data analytics for a healthy education life

Christina Karagianni[1,*], and Athena Vakali[1]

[1]1AUTH, School of Informatics, Thessaloniki, Greece

1. Work-in-progress

Introduction In recent years, ubiquitous devices have penetrated people's lives, and numerous studies have been conducted to find behavioral and emotional patterns affecting health and well-being [1],[2]. Especially in mental healthcare, till now, the tracking of the patient's conditions relied solely on doctor appointments and self-reported surveys, which are time-consuming and might lack objectivity. During their university years, students often suffer from accumulated stress. Thus, early diagnoses and improved monitoring are becoming vital. Exploiting the StudentLife dataset [3], a structured approach to predict the self-reported PANAS [4] Negative Affect (NA), consult students and reduce university drop-outs is briefly introduced.

Data Sources The StudentLife sensing app captured the daily impact of assignments on the activity, mood, sociability, well-being, and academic performance of 48 students throughout the semester. The StudentLife dataset contains sensor data, Ecological Momentary Assessment (EMA) [5], survey responses, and educational data. The first results show significant correlations between smartphone objective sensor data and the student body's mental health and academic profiles. The PANAS questionnaire is a frequently used instrument assessing positive and negative affect and, in our work, serves as the ground truth.

In this work, we explore the data types presented in Table 1 and investigate if we can predict NA from the objective sensing data. Additionally, there are data depicting academic performance, reporting the Grade Point Averages (GPAs), and the usage of the student forum called Piazza.

Table 1.
The sensing data objectively track the everyday behaviors. The data related to the academic performance capture the educational profiles. The PANAS NA serves as our ground truth.

Sensing Data				Academic Performance		Self-Reported Data
Activity	Sociability	Sleep	Location	GPAs	Piazza	PANAS NA
stationary	calls / sms	dark	bluetooth	gpa all	days online	
walking	voice	silence	wifi	gpa 13s	views	
running	noise		dinning place	gpa cs 65	contributions	
	cnversation				questions	
	phonecharge				notes	
	phonelock				answers	

Discussion The analysis starts with integrating and preprocessing all data types. So far, we have evaluated the performance of state-of-the-art Machine Learning (ML) approaches. Fig. 1 presents the Pearson correlation coefficients between the features (on the left) and the ML models' performance (on the right). The preliminary results of this study show a significant positive correlation between the student's grades and their negative feelings. Moreover, the

Persuasive 2023, Adjunct Proceedings of the 18th International Conference on Persuasive Technology, April 19–21, 2023, Eindhoven, The Netherlands
*Corresponding author.
kechristi@csd.auth.gr (C. Karagianni); avakali@csd.auth.gr (A. Vakali)
0000–0001–5772–3187 (C. Karagianni); 0000–0002–0666–6984] (A. Vakali)

Random Forest (RF) regressor best predicts PANAS NA. We plan to move to a Deep Learning Architecture as a next step. Additionally, we intend to study specific social groups separately, e.g., males and females, first- and second-gen university students, capturing personalized contexts of college students.

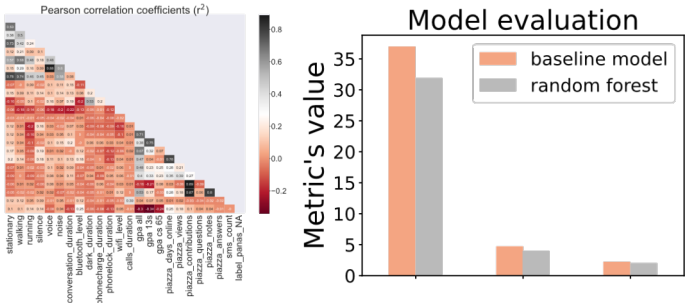

Figure 1. The correlation matrix (on the left) depicts that the PANAS NA is positively correlated with GPA, meaning the lower the student's GPA, the less happy they feel. The preliminary results from the RF regressor compared to the dummy classifier (baseline model) are shown on the right.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skl odowska Curie grant agreement No 813162. The content of this paper reflects only the authors' view and the Agency and the Commission are not responsible for any use that may be made of the information it contains.

References

[1] Gabriella M. Harari, et al.: Patterns of behavior change in students over an academic term: A preliminary study of activity and sociability behaviors using smartphone sensing methods, Computers in Human Behavior, Volume 67, Pages 129-138 (2017).

[2] Harari, G. M., et al.: Using Smartphones to Collect Behavioral Data in Psychological Sci-ence: Opportunities, Practical Considerations, and Challenges. Perspectives on psychological science : a journal of the Association for Psychological Science, 11(6), 838–854 (2016).

[3] Rui Wang, et al.: StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones. ACM International Joint Conference on Per-vasive and Ubiquitous Computing (UbiComp '14). Association for Computing Machinery, New York, NY, USA, 3–14 (2014).

[4] Watson, D., Clark, L. A., Tellegen, A.: Development and validation of brief measures of positive and negative affect: The PANAS Scales. Journal of Personality and Social Psychol-ogy, 47, 1063–1070 (1988).

[5] S. Shiffman, et al.: Ecological momentary assessment. Annu. Rev. Clin. Psychol., 4:1–32, (2008).