Reiew of the Paper

Student: Yunfei Luo

May 19, 2020

Personalized Student Stress Prediction with Deep Multitask Network
by Abhinav Shaw, Natcha Simsiri, Iman Deznabi, Madalina Fiterau, Tauhidur Rahman
Reference Paper URL: https://arxiv.org/abs/1906.11356

Introduction/Main Goal

This paper was published in 2019. The main goal of this paper is to provide a solution for personalized modeling on the prediction of level of stress. The data was collected from a program in Dartmouth college, with volunteer students wearing sensors and completing surveys.

What's New/Improvement

This paper was motivated by the previous work *Towards deep learning models for psychological state prediction using smartphone data: Challenges and opportunities* by Mikelsons, G., Smith, M., Mehrotra, A., and Musolesi, M. "However, it doesn't address the challenges of inter-subject variability or heterogeneity in granularity." (Section 1 of the paper). This paper approach the problem with inter-subject variability by modeling for each individual, and the problem with heterogeneity in granularity by implementing Auto-Encoder with LSTM.

Observations

The overall learning process is a supervised learning, with the data from sensors as input, and result from surveys done by students as known output. For having better performance, some intuitively related Covariates, including time till next due, the rating and duration of sleeping, were concatenate to the input sensor data.

Furthermore, in order to deal with the long sequence and moise in the raw data from sensors, the raw data was first converted to bins with 1 minute long, then to histogram of a period of one hour. The hidden features was learned by the Auto-Encoder with LSTM. Then, these output features will be sent to the supervised learning model for further processing.

The loss function was defined by the sum of Mean Absolute Error(MAE) of Classification Error(CE) from the supervised learning, and Reconstruction Error(RE) from the decoder of the Auto-Encoder, with hyperparameters α and β (Equation (1) in section 3.2.4):

$$\alpha \, RE + \beta \, CE$$

The output (predicted labels) are *below median stress, median stress, and above median stress*

(Section 4 of the paper).

Result
The performances (F1-score) of using different models are shown below, include location-based MLP, LSTM, and CALM-Net. (Table 1 of the paper):

Table 1. F1 scores of stress level prediction on StudentLife dataset.

Model	F1-score
Location-MLP	0.408
LSTM	0.426
Most Common Label	0.551
LM-Net	0.586
CALM-Net No covariates	0.571
CALM-Net	**0.594**

Where CALM-Net have the best performance on this dataset.

Extension/Follow up
The possible extension would be try different models in Auto-Encoder, such as GRU-D, to see if there is improvements in the prediction result. Moreover, try clustering the students would be helpful, so that not much data needed from predicting the level of stress of new students.