Reflection: Timeseries Classification with HA-TCN for Stress Levels

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1 Introduction

This project aims at re-implementing the work previously done by *Lin et al., 2019* on the paper *Medical Time Series Classification with Hierarchical Attention-Based Temporal Convolutional Networks: A case study of Myotonic Dystrophy Diagnosis*. While this invention focuses on the interpretable diagnosis of myotonic dystrophy from analysis of handgrip time series data, we propose that this model can also be used for time-series data for measuring stress levels. We believe that an HA-TCN model can predict levels of stress based on heart rate monitoring at different time-steps, further demonstrating that this model has applicability beyond its current use.

2 Challenges

In the development of this project, we encountered some challenges that were addressed with time and extensive research:

- Our goal in this project was to re-implement *Lin et al., 2019* paper by considering it in a different scenario: predicting stress based on heart levels. However, we had to spend sometime understanding how to create the appropriate labels in our data to differentiate an observation from stress and no stress. This challenge was resolved by researching and understanding thresholds of heart rate and other variables. In doing so, we created a model labels that were assigned for each timestamp based on the heart rate behavior within a particular period.

- Convolution models tend to become messy and difficult to understand as our data gets passed into several convolving layers. Our task was to appropriately look into how to accurately represent our data at each step, while preserving its meaning for final prediction. Our consideration was to understand how our data was transformed by looking into dimensionality and appreciating how the model behaved through each convolution.

- The current challenge is to identify meaningful ways of visualizing the behavior of our model. We will providing further ideas in our paper on how this was resolved.

3 Insights

Our model is surprisingly performing well. While it has some extremely large fluctuation in the losses at the beginning of training (the first batches), it is able to lower its loss and carry out experiments consistently with an average of 95 % accuracy.

4 Plan

As of today, we are looking into how to visually represent the behavior of our model and provide some summary statistics. Furthermore, we are interested in finding more rigorous approaches for creating our labels beyond a binary classification – 0 or 1 to indicate stress levels.