CE889– Neural Network and Deep Learning

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Abstract

Nowadays, there are lots of different neural network architectures developed. This network checks the working of the human brain. Many applications use this network like Medical, Autonomous car development, Speech or Text recognition, etc. We classified workload using a dataset given by the professor which is generated by EEG signal. We will identify this using the simple logistic model and deep learning model. We will compare and discuss the result of both models.

Background

Reading and finding the actions of the human brain is the most difficult and complex task. But it is somewhat easy to use an interconnected neural network [1]. There is three primary types of neural system – Artificial Neural Network, Convolution Neural Network, Recurrent Neural Network. All this is used for different types of applications like ANN with tabular data, RNN with sequence data(time series, text, audio), CNN with image data. Nowadays, the mental workload has popular in many fields such as neuroscience [2] [3], human factors and ergonomics [4], and human factors in computing systems [5]. There are various signals used to gauge mental burden like neurophysiological, electroencephalogram, electrocardiogram, electrooculogram. But from all these EEG signals are the best for load assessment [6]. The NASA Task load index [7] is the most established one for retrospectively assessing an entire task for the physical and mental load. The Instantaneous Self Assessment (ISA) [8, 9] scale was created to permit members to rapidly report mental responsibility on a straightforward Likert scale. A recognized consequence of this technique is that self-reporting mental workload during a task can act as a secondary task that itself impedes the performance of the primary task [10]. Thus, much work has focused on physiological estimations to appraise mental responsibility [11]. Each sample in our dataset consists of four synchronized measurements: Eye tracking, Functional Near-Infrared Spectroscopy [11, 13], Galvanic Skin Response [12], photoplethysmography.

Methods

We have used a logistic model and a deep learning model for the classification of mental workload. Dataset was given by the professor. Firstly, we have read data from the Matlab file. We have used the scipy library to load and read data. Then after we separate data and labels. There are 180 samples for 2 classes so a total of 360 samples. We have split data into 80% train and 20% test. After that, we have to change the shape because we want samples as columns. We have defined one class in that we define a function for feedforward, backpropagation, sigmoid, accuracy. We have done a dot product of train data and weights and perform sigmoid on that. Find error and update bias and weight. Find accuracy for that model. We have created a deep learning model. Add a dense layer of (128,64,32,16,8,2) dimension. Add relu and softmax function with activation layer for every dense layer. We have added the dropout function for every layer with 0.1 and 0.2. This will help with the overfitting. We have used mse(multiscale entropy) for loss, accuracy metrics, and adam optimizer for compile model. The fit model with 10 epochs and batch_size 64. Use 5 – fold cross-validation for evaluation using accuracy score. We have also tried KNeighborsClassifier with n_neighbors = 10 for the classification model of neural networks.

Results

We have compared results with accuracy between these models. We got 83% test accuracy in the logistic model, 50% with the KNeighborsClassifier model, and 51% with a neural network model.

Conclusion

From the above result, We conclude that try with different other models. We need to add or remove some layers in our model and add some feature selection and extraction methods with this model.

Reflections

In the future, I would like to perform other operations and try to get good accuracy with this dataset. I need to get more understanding about data and prepare models accordingly.

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