EC ENGR C247 – Final Report

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Abstract

This study applied different neural network architectures to decode the electroencephalography. The best accuracy was 70% achieved by one of the neural network architectures. I discovered the study needs more raw data that is not replicated from the original dataset will help achieve more realistic results. Hyperparameters also play an important role to contribute high accuracy at training/validation as well as testing phase.

Introduction

Since the EEG has relatively poor spatiotemporal resolution compared to other neural recording techniques, using CNN architecture and CNN combined with other machine-learning components is quite suitable for this study. CNN is well suited for end-to-end learning from raw datasets and brain signal decodings such as EEG. In this study I am going to investigate how CNN or hybrid CNN performs with the datasets provided from the project.

Results

Performance from ConvNet: 65%

Activation functions: ReLu

Pooling mode: Mean

Regularization and intermediate normalization: Batch Normalization and Dropout

Factorized temporal convolutions: Two 6x1 convolutions per convolutional layer

one-step convolution in first layer

Hybrid CNN+LSTM with BiDirection model: 70%

Activation functions: eLu

Pooling mode: Max

Regularization and intermediate normalization: Batch Normalization and Dropout

Factorized temporal convolutions: One 5x5 convolution per convolutional layer

LSTM combined with bidirectional model at the FC + LSTM layer

Hybrid CNN + RNN: 67%

Activation functions: ReLu

Pooling mode: Max

Regularization and intermediate normalization: Batch Normalization and Dropout

Factorized temporal convolutions: One 5x5 convolution per convolutional layer

RNN at the CNN+RNN layer

Discussion

Hybrid CNN+LSTM with BiDirection model performed the best among three models. After all input finally arrives at the LSTM layer. It processes all input from the previous layer to the short term memory and transfers them to the long term memory for prediction. Furthermore, Bi-LSTM stores input from the past and future context. It is majority used in NLP but somehow it is also suitable for using it with CovnNet. This combination allowed the model to capture image data from the past and future for better class prediction (even with data replication from the original dataset that may impact the truthfulness of the prediction outcomes). The study shows CNN is one of the few best tools suitable for decode low resolution graphs such as EEG. The performance can be robust with other machine learning methods and well tuned hyper-parameters.

References

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Keras Documentations:

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