 DOI: 10.3217/978-3-85125-962-9-167

Cross-dataset Few-Shot Learning for Motor Imagery BCI classification

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Although promising for many applications, current BCI systems still suffer from several limitations. Indeed, there is a gap between the performances obtained in laboratories and those obtained in practical use. In general, to reduce this gap, a long calibration to adapt the device to a new user is required. This makes BCI democratization in real applications difficult. Several works have focused on this problem proposing various type of approaches. However, the cases treated often lack realism compared to real applications (e.g. the test dataset has a recording setup close to the training data and/or the method relies on unlabeled data collected from the test subject). Moreover, there is currently very little work on cross-dataset transfer learning. To address this gap, the NeurIPSBEETL Challenge [1] has recently proposed a framework to evaluate transfer learning algorithms on both unseen subjects and datasets. We believe that this is a very good starting point to evaluate EEG signal classification algorithms in close to real life conditions. For this purpose, we rely on an experimental framework similar to the BEETL Challenge, with additionally simulating an even more restricted access to data.

On the other hand, low data regimes are not specific to BCI systems, and the field of Few-Shot Learning (FSL) has emerged to deal with these settings. The work in this field aims at classifying a large amount of unannotated data, by training a model on a few annotated examples. In our work, we propose to build on recent advances in FSL to establish an efficient model for cross-dataset MI classification. Based on an efficient Neural Network architecture, that leverages simple 1d convolutions layers, and using standard FSL training routines, we train a robust Deep Learning backbone on a large set of different datasets. This backbone is then used to extract relevant features to perform EEG signal classification, in setups with very few shots (e.g. 1/5/10/20, n-shot meaning that we have n labeled trials per class).

We evaluate the efficiency of our method by comparing it to standard transfer baselines (e.g. Fine-Tuning the backbone on few data of the new subject), as well as non Deep-Learning based baselines. We evaluate its robustness by experimenting on several open-source datasets. Some preliminary results are shown in Fig. 1.

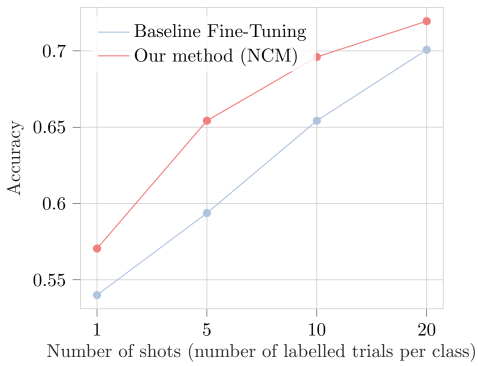

Figure 1: *Preliminary results, using a the BEETL Challenge setup, with Zhou2016 [2] as target dataset.*

Experimental results showed that our method can significantly reduce the amount of training data required to achieve a given level of performance. We believe that our work will help designing BCI systems quickly adaptable to a new user, for any given EEG recording setup.

References

[1] Xiaoxi Wei and al., "2021 beetl competition: Advancing transfer learning for subject independence & heterogenous eeg data sets," *arXiv preprint arXiv:2202.12950*, 2022.

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 Article ID: 144561