## Using General-Purpose Meta-Learning Algorithms to Train a BCI Classifier on Less Data

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*Introduction:* Meta-learning enables using the prior experience of the neural network from previously learned tasks to improve performance on a new task. In BCI-related applications this means the ability to use data from previous users to reduce the amount of data needed to train on new users as well as improve the quality of classification. An important advantage of *MAML* [1] and *Reptile* [2] meta-learning algorithms is that they can be easily applied to most neural networks based on gradient descent. In comparison with the classical pre-training, these algorithms allow better optimization of the starting weights for training on a new task, and also better generalize the starting weights on the training set of tasks [1].

*Methods:* We used the *EEGNet* [3] as the classifier and *MAML* [1] and *Reptile* [2] as meta-learning algorithms. The classifier was separately applied to the EEG data from 13 participants recorded in study [4], where two classes of 19-channel EEG epochs were collected: related to intentional eye fixations used to make actions in a gaze-controlled game and related to unintentional, spontaneous fixations. A meta-*EEGNet* model was trained using a meta-learning algorithm on the data of all participants except one which we call the test participant. In the tuning phase the model was trained on 50% of the test participant data and finally tested on another 50%. The baseline *EEGNet* was trained on 80% of the data of this participant and tested on another 20%.

*Results:* Group averaged ROC AUC was  $0.70\pm0.10$  (M±SD) for the baseline *EEGNet*,  $0.75\pm0.09$  for the *MAML-EEGNet* and  $0.69\pm0.07$  for the *Reptile-EEGNet*. The difference was not significant, according to Wilcoxon signed rank test (p = 0.17 and p = 0.41, respectively).

*Discussion:* With prior meta-learning, training on 50% of participant's data enabled comparable or better classification performance relative to the basic classification algorithm trained on a larger subset, i.e., on 80% of data.

*Significance:* The results provide initial evidence for the effectiveness of the *Reptile* and *MAML* meta-learning algorithms in training a BCI classifier for new users. As these algorithms can be easily applied to a wide range of neural network classifiers, they may appear as prospective tools for reducing the amount of training data that need to be obtained in a new user to achieve a reasonable performance.

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## References

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