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Sequential Forward Selection (SFS) for Transfer Learning Source Selection in Motor Imagery BCI

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Introduction: The tedious process of calibrating a brain-computer interface (BCI) for control creates a barrier to the adoption of this technology, especially for children who have been neglected from fundamental BCI research despite high user need. Transfer learning leverages previously collected BCI data from other users (sources) to reduce the calibration needed to train a classifier for a new user (target) [1]. However, not all source data is beneficial, and some can be detrimental to the training of a new classifier. Despite this understanding, little work has been done to investigate what factors influence the 'transferability' of a source. One assumption is that the users with the highest within-session (WS) classification performance should be the most beneficial. We challenge this assumption by comparing the transfer learning with the top WS performers to a technique called sequential forward selection (SFS).

Materials and Methods: For this investigation we used previously collected left/right motor imagery data from 32 children [2]. We aimed to compare the performance of 3 source selection methods. First, the WS ranking method includes the top sources based on their within-session classification accuracy. Second, individual SFS started with an empty subset and iteratively added the source which most improved the AUC score. This continued until all sources were included. Third, SFS ranking attempted to build a measure of transferability, based on the SFS subsets, such that sources were ranked by how early, on average, they were added to the source subset. All methods used the same Riemannian recentering method for transfer, and minimum distance to the Riemannian mean for classification [1].

Results: Fig. 1 shows how the classifier AUC score varied with different methods and with subsets of different sizes. As expected, scores converge when all 31 sources are included. WS ranking method declined with the addition of the 6^{th} and 7^{th} ranked sources, indicating that these sources have poor transferability despite strong WS performance. Individual SFS demonstrated the strongest performance and did not include these detrimental sources until necessary. SFS ranking nearly matched individual SFS in terms of AUC score and does not include the detrimental sources until necessary.

Conclusion: WS performance is not always a good indicator of transferability for children performing motor imagery. Individual SFS is more robust and achieves higher AUC scores but has the tradeoff of requiring more target data to evaluate subsets. SFS ranking balances high AUC scores without requiring target data for evaluation. This work motivates greater investigation into other data-driven methods for source selection.

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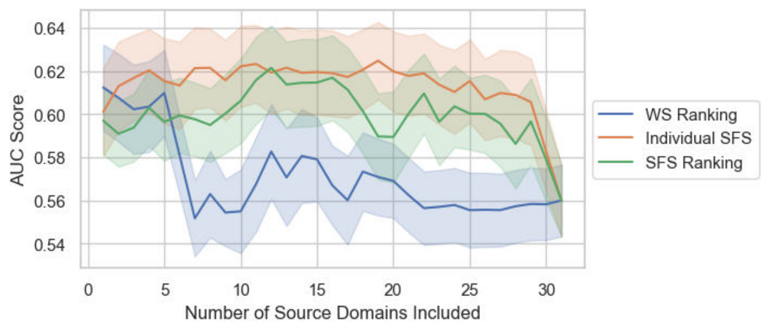

Figure 1: A plot of the AUC scores of different source domain selection methods with increasing numbers of included source subjects. Bold lines indicate the mean and shaded areas indicate the standard error of the mean (SEM).

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