Predicting Neurofeedback Performance

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1 Introduction

Self-regulation performance in real-time fMRI-based neurofeedback shows large inter-individual and inter-study variation. Clear learning curves are seen rarely. Using machine learning, we investigate whether neurofeedback regulation performance is largely random or follows predictable patterns across runs.

2 Methods

We used a machine-learning approach (LASSO regression, cross-validated) to predict regulation performance of a run based on performance in previous regulation runs. For each regulation run as target, we report the coefficients of determination of the obtained LASSO Models.

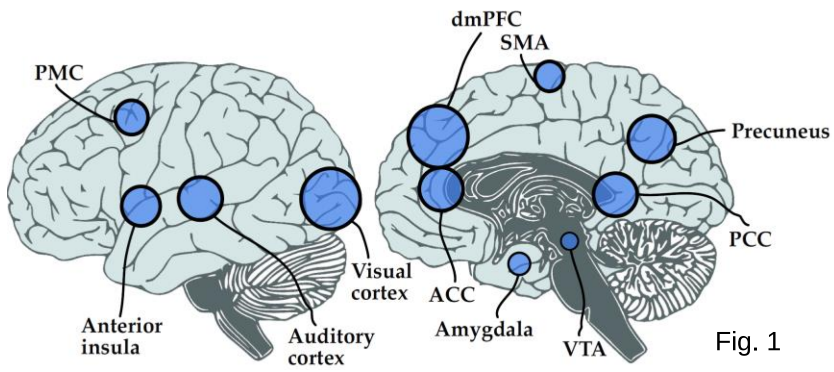


Fig. 1

The dataset consists of 12 studies including a total of 182 participants and 10 different ROIs. Neurofeedback regulation performance was measured in percent signal change.

3 Results and Discussion

Overall, participants successfully performed percent signal change regulation (positive % signal change during regulation compared to baseline, Fig. 2-5). However, the machine-learning prediction results are mixed. The obtained median R^2 values are above 0 for each run (median R^2 = 0.12 - 0.22), but a few poorly performing models reduce the average R^2. Furthermore, there is no clear pattern of which past runs are most important for the prediction (Fig. 7).

3 Results and Discussion – continued

Fig. 2

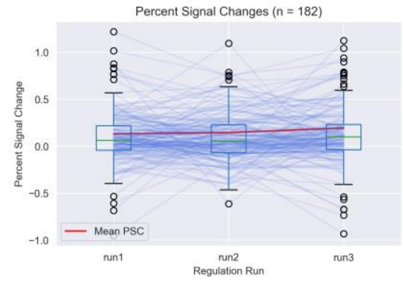


Fig. 3

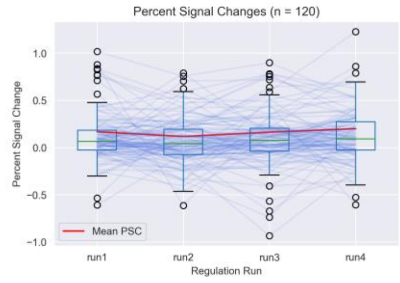


Fig. 4

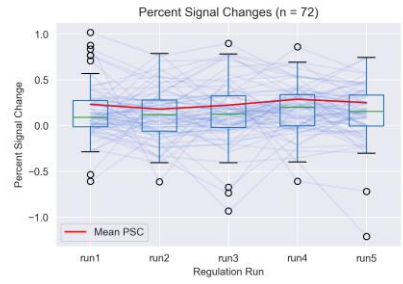
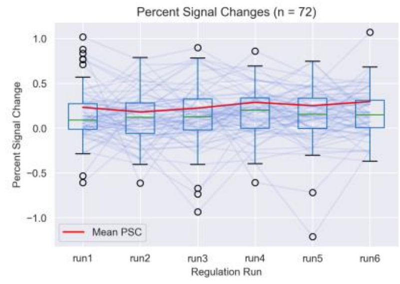


Fig. 5



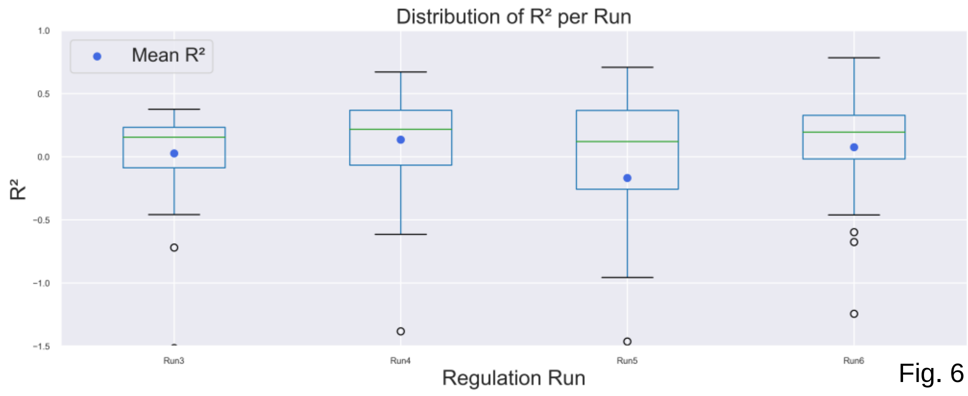


Fig. 6

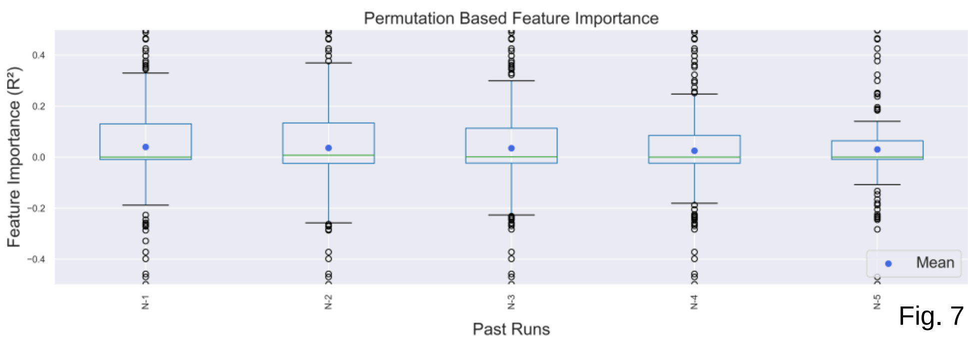


Fig. 7

4 Conclusion

Participants in real-time neurofeedback training studies are able to self-regulate brain activity. Also, regulation performance is, at least to some extent, predictable from previous run performance. This indicates that neurofeedback training induces systematic changes. The next steps will be to (1) extend our dataset, (2) optimize the current analyses with non-linear models, and (3) add information from other features that have been shown to influence neurofeedback performance (see our Poster # 60: Factors influencing neurofeedback performance and learning success: A Machine Learning Mega-Analysis).

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