

Factors influencing neurofeedback performance and learning success

A MACHINE LEARNING MEGA-ANALYSIS

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Background

Inter-individual differences in neurofeedback (NFB) performance and learning success are large, and some individuals do not benefit from NFB training. The main factors that cause this large variability in NFB performance and learning success are unknown.

Methods

In a sample of 29 NFB studies with 599 participants, we investigated the influence of 31 different features related to experimental design, imaging parameters, demographics, etc. on NFB learning success and NFB regulation performance (this latter analysis included only studies that reported % signal change).

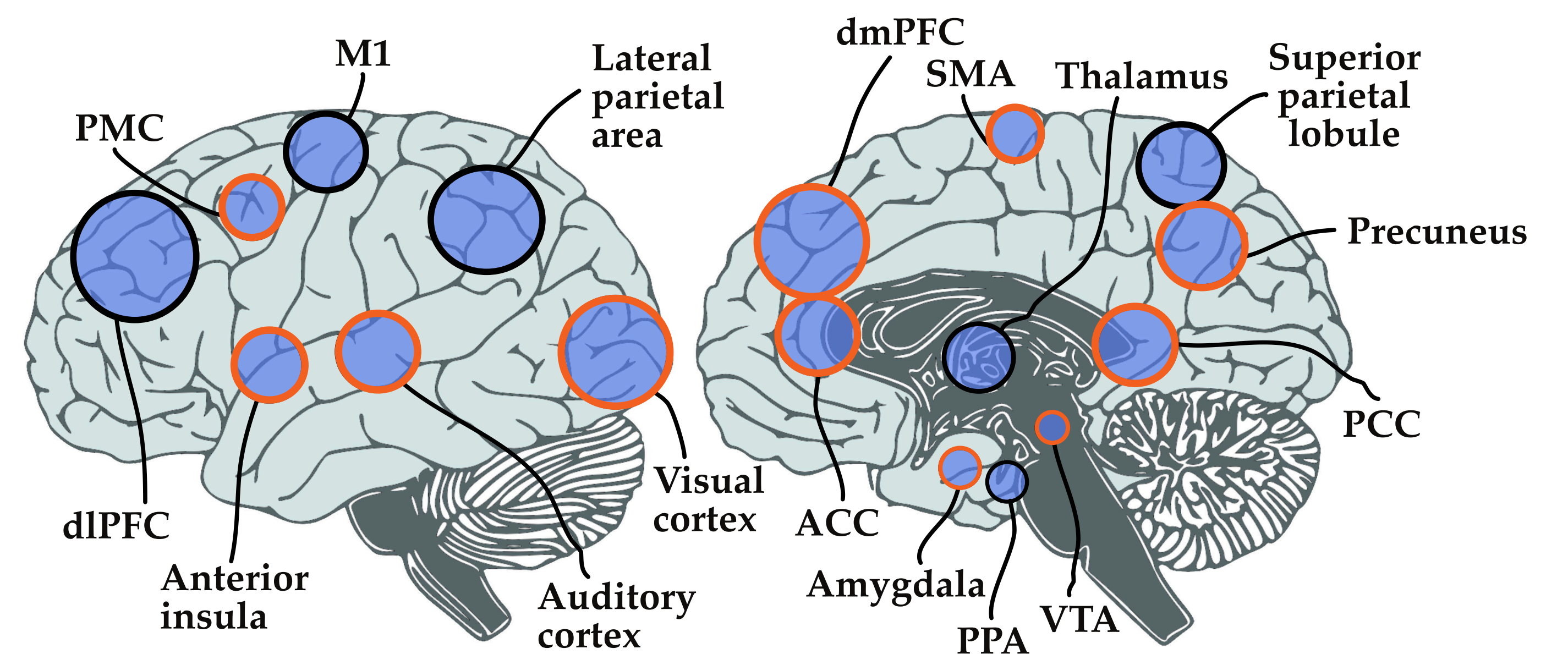
Predictions were based on 3 different machine-learning methods:

- an ordinary least squares model with lasso regularization (LASSO)
- a random forests model (RT)
- an extreme gradient boosted trees model (XGB)

We used cross-validation (10 times 10-folds) to avoid overfitting and to assess generalizability.

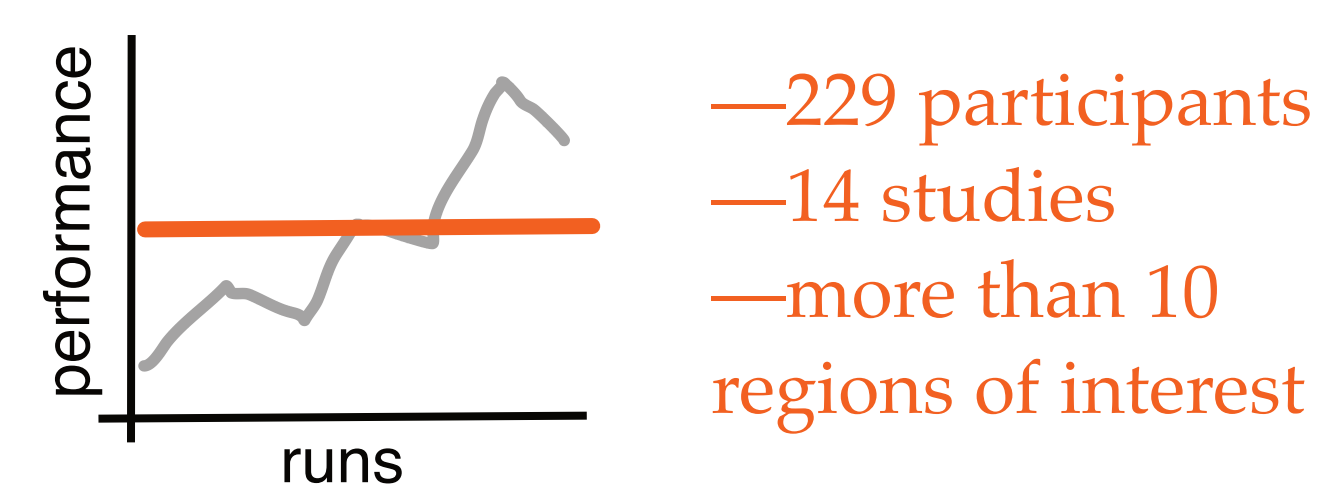
Feature importances were first calculated for each model type and, then, weighted by the corresponding model's R² values and averaged over all 3 model types.

Mega-analysis



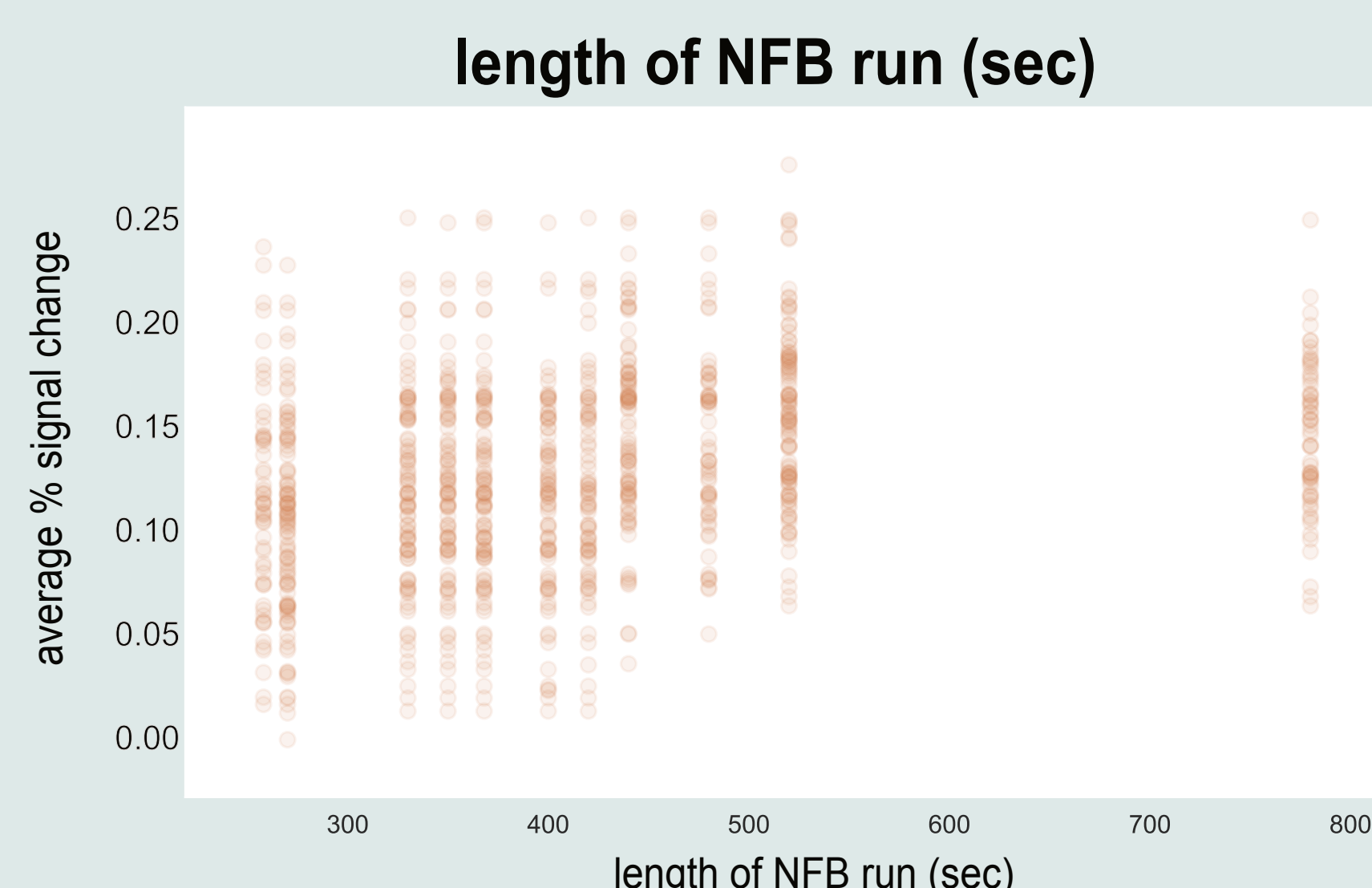
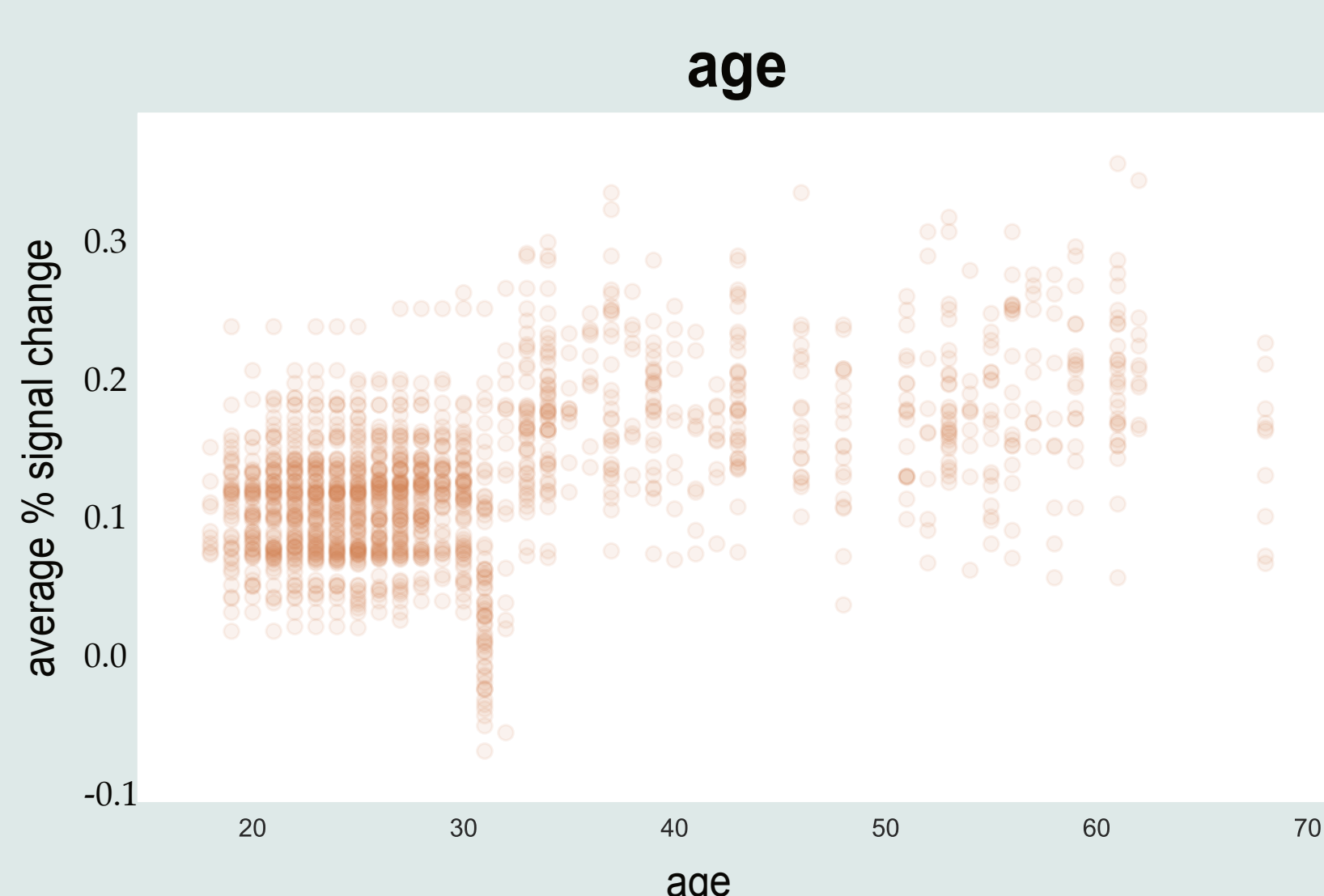
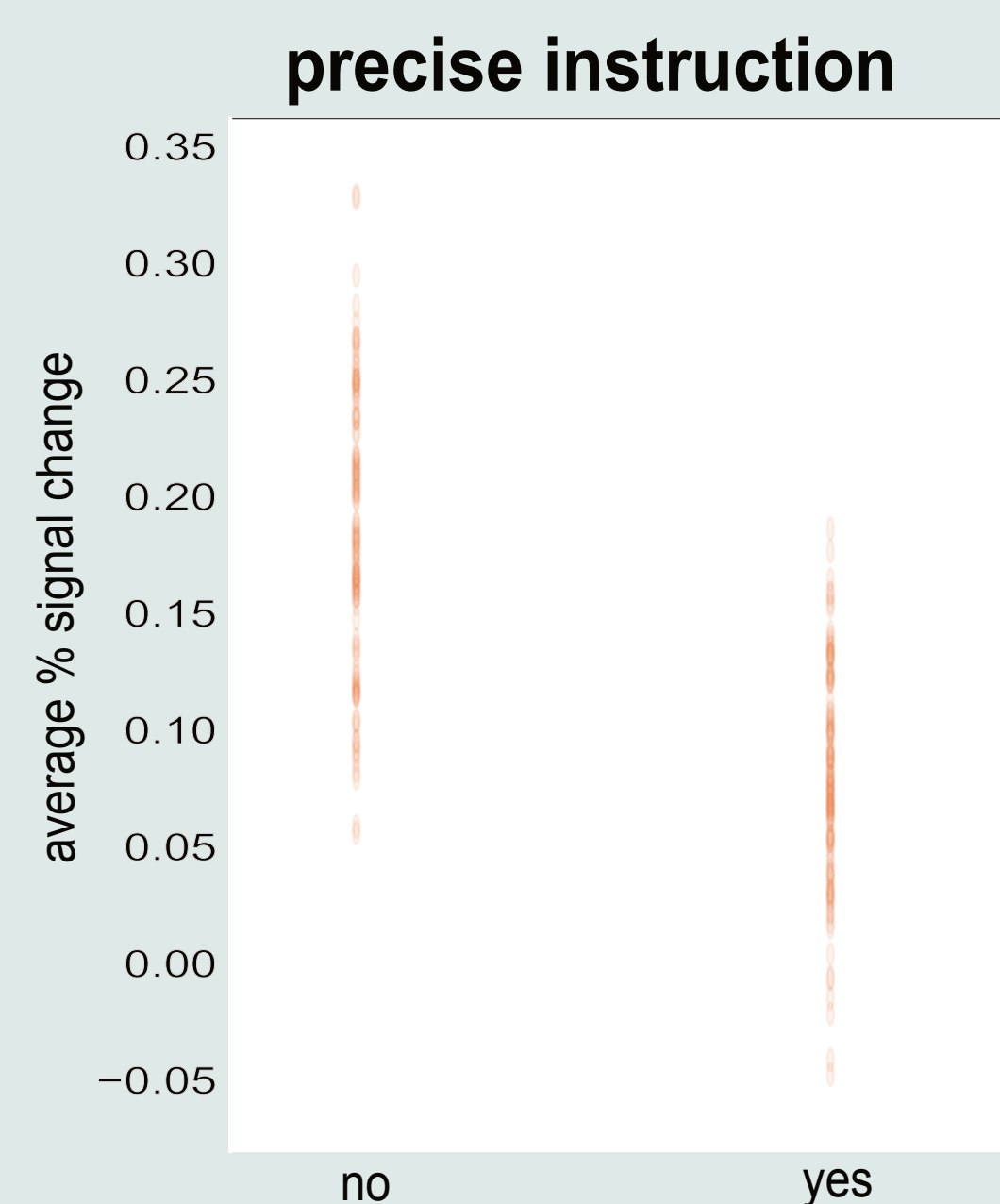
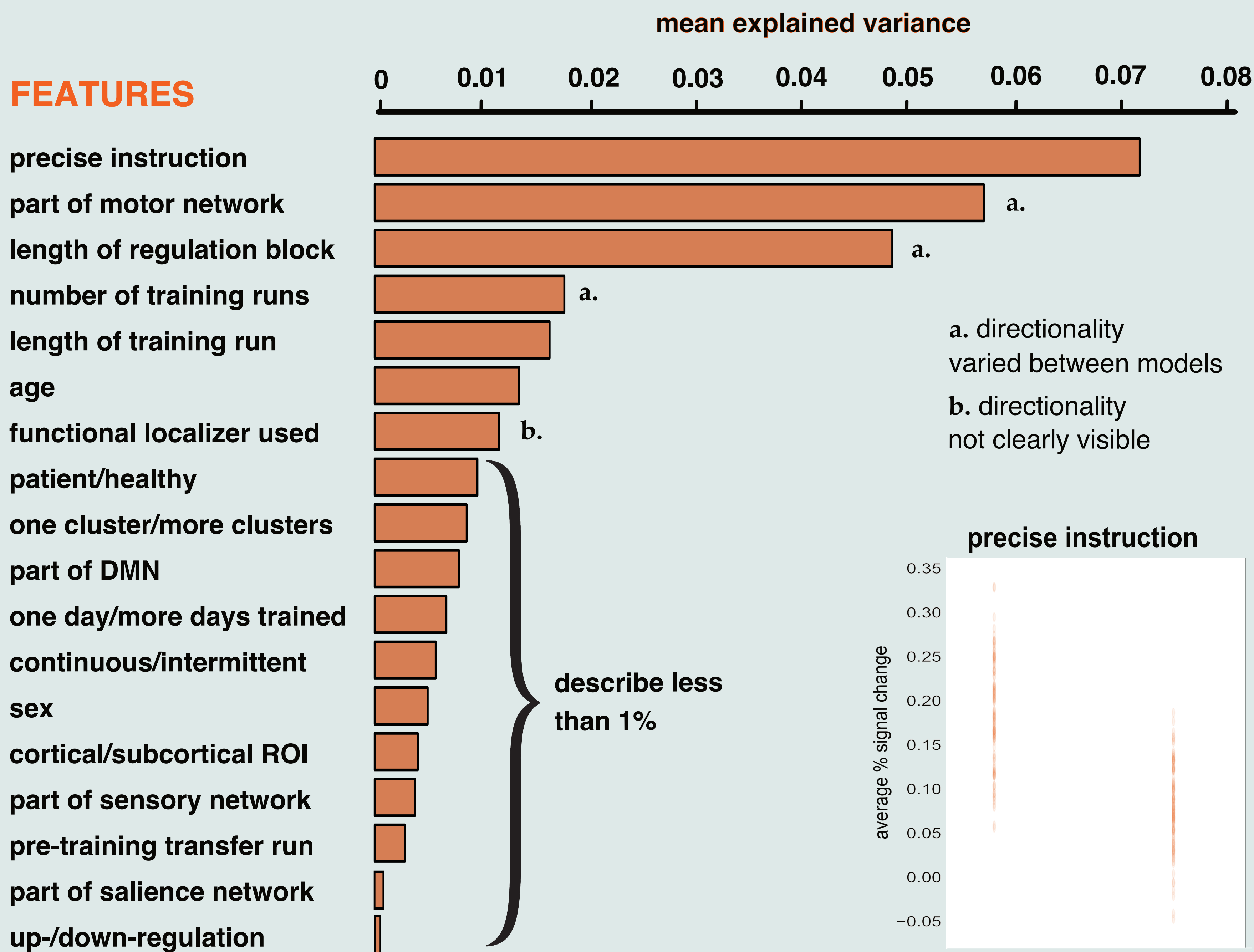
○ Analyses on NFB performance (mean % signal change of all NFB runs)

● Analyses on NFB learning success (slope over all NFB runs)



Results: factors influencing NFB performance

Models aiming to predict NFB performance explained variance of R² = 0.31 for the LASSO model, R² = 0.26 for the RT model, and R² = 0.31 for the XGB model. Feature importances varied between linear and non-linear models (see figures below).



Results: factors influencing NFB learning success

Overall model performance was very weak, where, on average, no variance was described by the models (LASSO: average R² = -0.04, RT: average R² = -0.02, XGB: average R² = -0.02). Therefore, feature importances for features influencing NFB learning success were not further investigated for the three models.

Discussion

Interestingly, our models were not able to explain any variance when we targeting NFB learning success (see poster #119 for a mega-analysis of NFB learning and overall NFB learning curves). In contrast, the models explained approximately one third of the variance for the NFB performance target. These analyses can help to design more efficient NFB studies.

To further improve the model predictions and better identify key performance and learning parameters in NFB experiments we will

- (1) improve the target measures (especially the definition of learning)
- (2) include additional features that might influence NFB learning success and performance
- (3) include more data

Looking for contributions!



These analyses were only possible due to contributions from many researchers. You have conducted a rfMRI study? We are happy about any further data contributions, so we can increase generalizability and investigate even more features!

Please contact us: amelie.haugg@uzh.ch

Check out poster 119 for more mega-analysis results!

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