Mapping fNIRS to fMRI with Neural Data Augmentation and Machine Learning Models

2020 NeurIPS BabyMind Workshop

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2020.12.11

Content

Introduction

Neuroimaging

Neuroimaing is to measure the structure and function of the brain.

Neuroimaging Techniques

fMRI*

- Uses magnetic resonance
- Most widely used
- High costs
- Weak at head motion

*fMRI: functional magnetic resonance imaging

Magnetom; Siemens, Germany

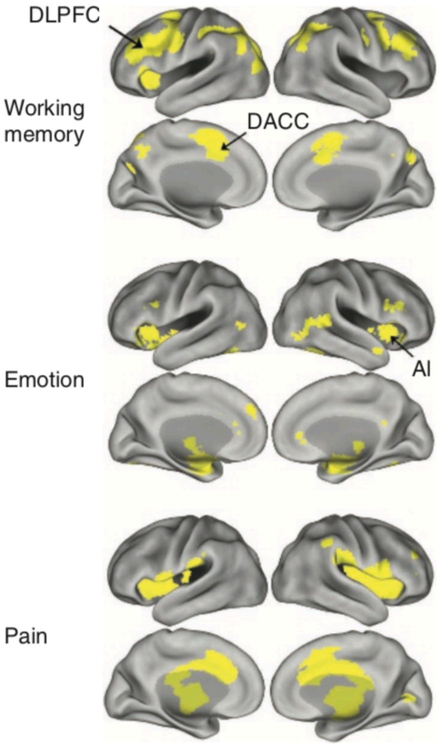
fNIRS*

- Uses near-infrared light
- Cheap and portable
- Strong at head motion
- Low spatial resolution

*fNIRS: functional near-infrared spectroscopy

NIRSIT; OBELAB, Korea

Neuroimaging Literature



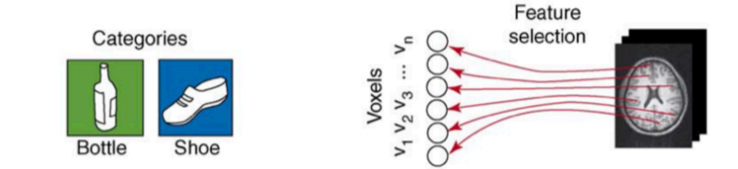
Large-scale automated synthesis of human functional neuroimaging data

Tal Yarkoni[1], Russell A Poldrack[2–4], Thomas E Nichols[5,6], David C Van Essen[7] & Tor D Wager[1] (2011)

“fMRI-based biomarkers”

Beyond mind-reading: multi-voxel pattern analysis of fMRI data

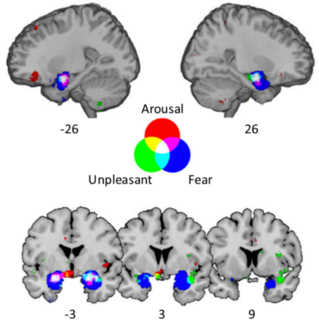
Kenneth A. Norman[1], Sean M. Polyn[2], Greg J. Detre[1] and James V. Haxby[1] (2006)



Review

Decoding the Nature of Emotion in the Brain

Philip A. Kragel[1] and Kevin S. LaBar[1,*] (2016)

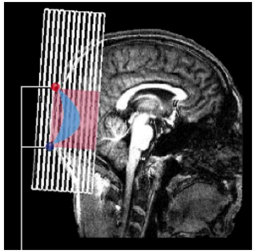


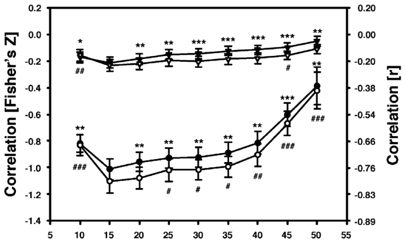
Needs for Finding a Mapping Function

Previous literature has focused on 1) simultaneously recording and 2) correlation.

Investigating the post-stimulus undershoot of the BOLD signal— A simultaneous fMRI and fNIRS study

Matthias L. Schroeter,[a,b,*] Thomas Kupka,[a] Toralf Mildner,[a] Kâmil Uludağ,[c] and D. Yves von Cramon[a] (2006)





Validating an image-based fNIRS approach with fMRI and a working memory task

Sobanawartiny Wijeakumar[a,*], Theodore J. Huppert[b], Vincent A. Magnotta[c], Aaron T. Buss[d], John P. Spencer[a,*](2017)

Research Needs

Obtain fNIRS and fMRI measures separately

Find a mapping function

Enable a direct mapping from fNIRS to fMRI measures

Objectives

01. To examine if different scanning environment impacts task performance

02. To find a mapping function between independently obtained fNIRS and fMRI measures

03. To utilize data augmentation and machine learning to build such model

04. To improve the plausibility of fNIRS as a potential surrogate of fMRI markers

Methods

Method I - *Participants, Design and Tasks*

Participants

- **50** (female: 21; male: 29)
- **Age**: 23.4 (mean)
- **Data exclusion criteria**
  - Head motions
  - Scanner issues
  - Poor performance

Experimental Design

Session 1

fNIRS

1-3 days

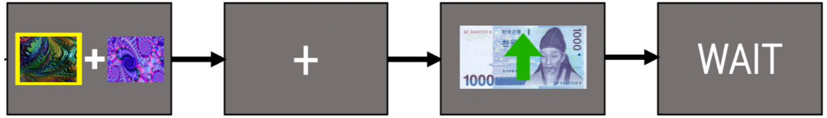
Session 2

fMRI

Tasks

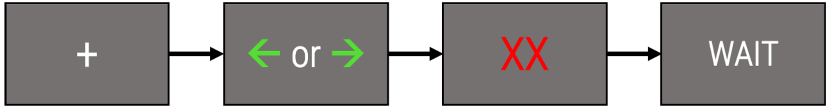
Probabilistic Reversal Learning (PRL)

(Hampton et al., 2006)



- Decision-making in a volatile environment
  - Measure of interest: *prediction error*

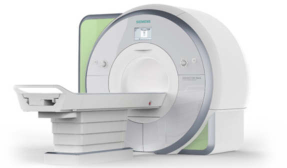
Stop Signal Task (SST) (Li et al., 2006)



- Response inhibition, an ability to inhibit action
  - Measure of interest: *successful stop*

Method II – *fMRI & fNIRS*

fMRI



Magnetom Trio;
Siemens, Germany

- Records the BOLD* signal
- 3T scanner
- Whole brain activity

*BOLD: blood-oxygen-level-dependent

GLM*

*GLM: general linear modeling

fNIRS

NIRSIT;
OBELAB, Korea

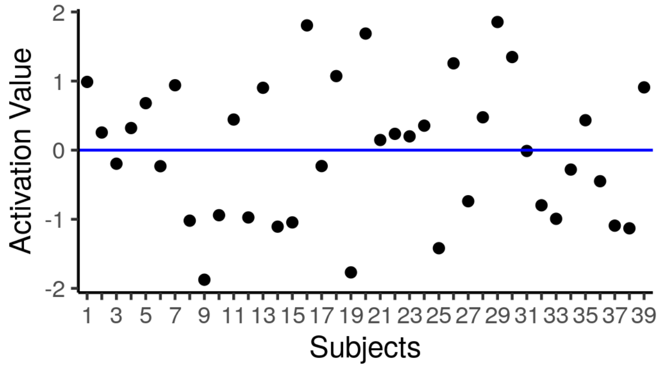
- Records HbO*, HbR* and HbT* signals (48 channels)
- Prefrontal brain activity

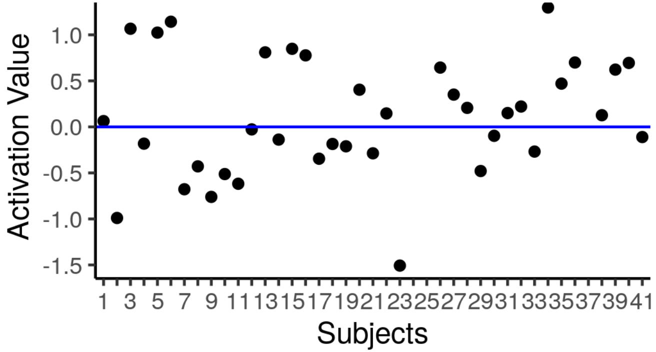
*HbO: oxygenated hemoglobin
*HbR: deoxygenated hemoglobin
*HbT: total hemoglobin

GLM

SST **Successful Response Inhibition**

Right Inferior Frontal Gyrus

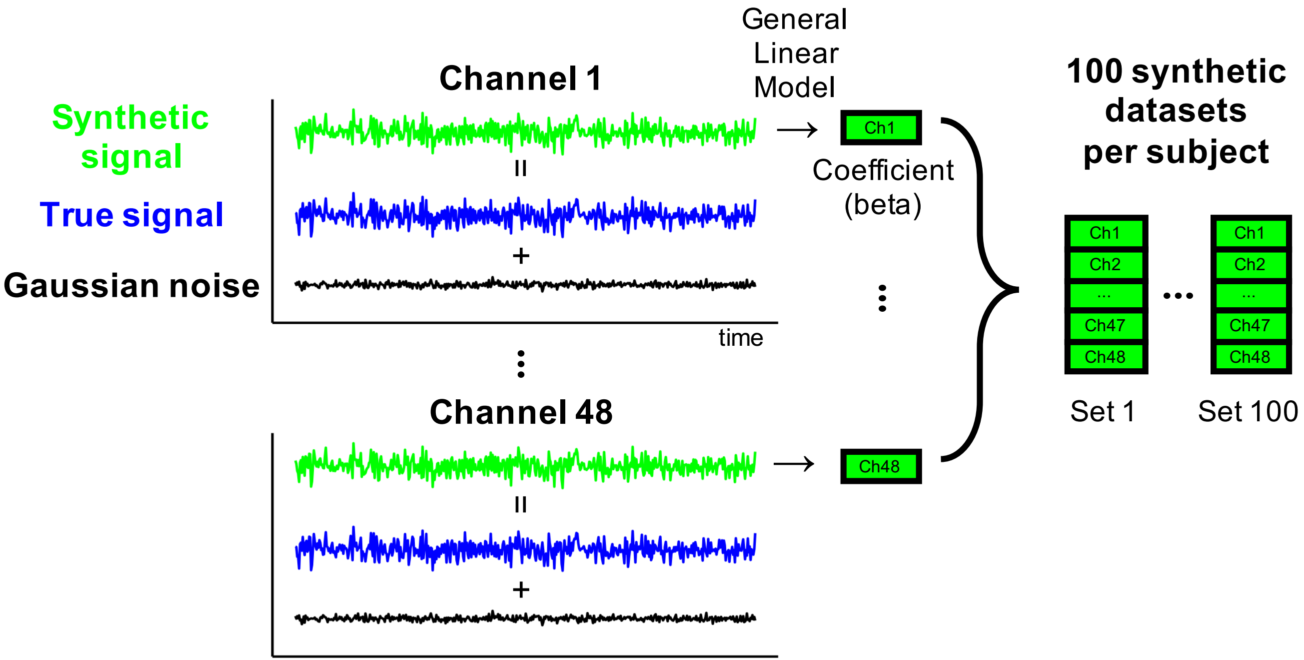




Method III - *Data Augmentation*

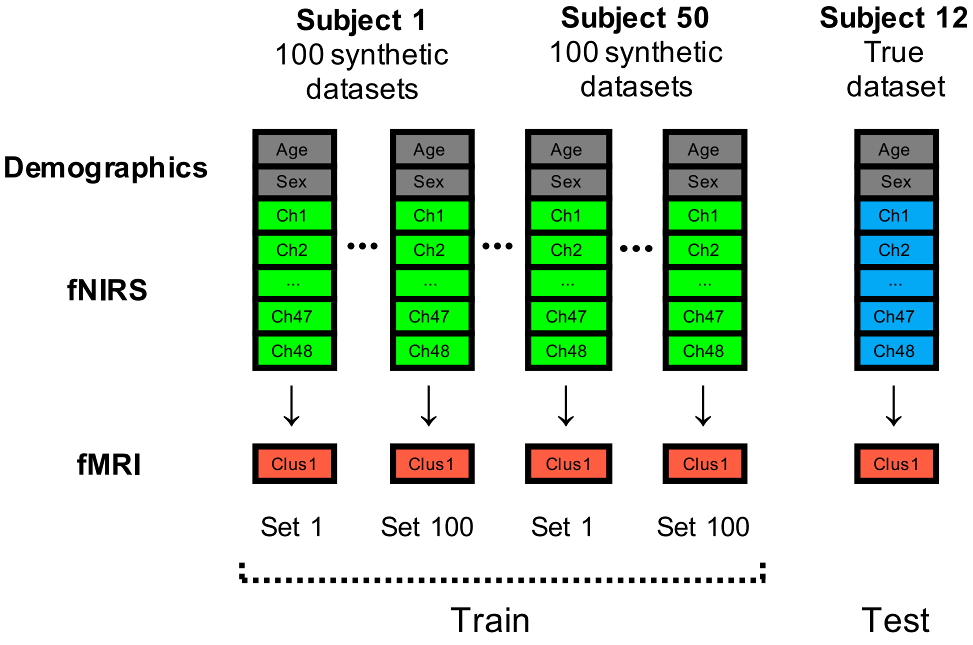
Data augmentation to generate synthetic data based on the true data

(Nagasawa et al., 2020; Safdar et al., 2020).



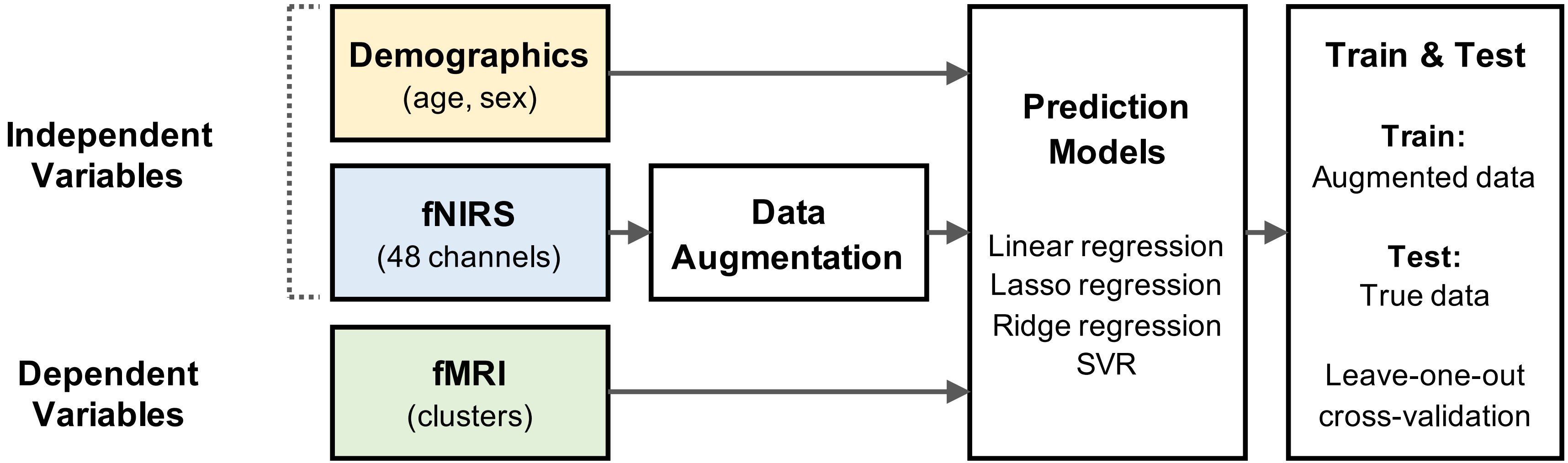
Method IV - *Leave-one-out cross-validation*

Leave-one-out cross-validation with the augmented and true dataset



Prediction Pipeline

Prediction with Data Augmentation and Machine Learning Models



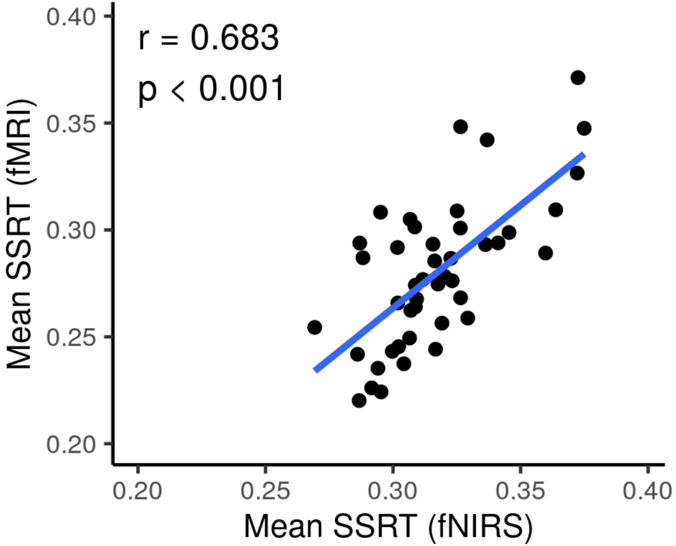
*SVR: support vector regression (with radial basis function; RBF)

Results

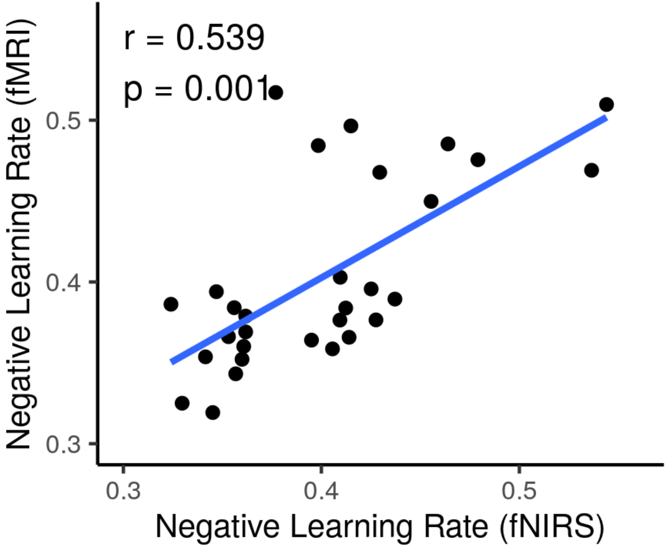
Result I – *Behavioral* Consistency

1 Scanning environment did not significantly impact task performance.

SST Stop Signal Reaction Time



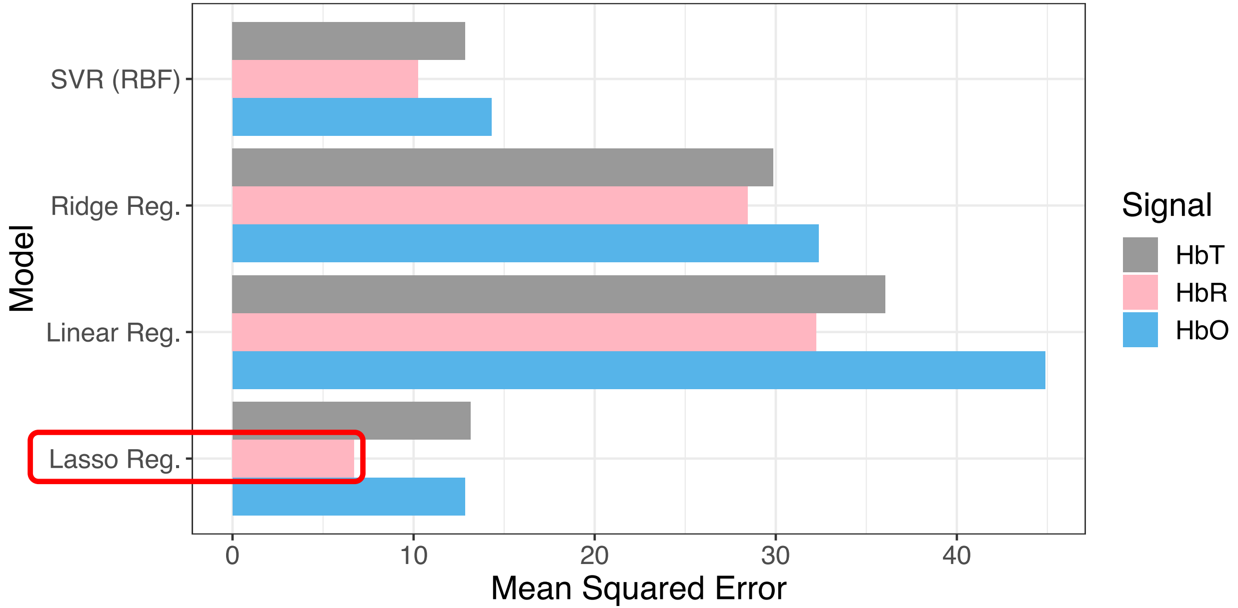
PRL Negative Learning Rate



Result II – *SST Model Comparison*

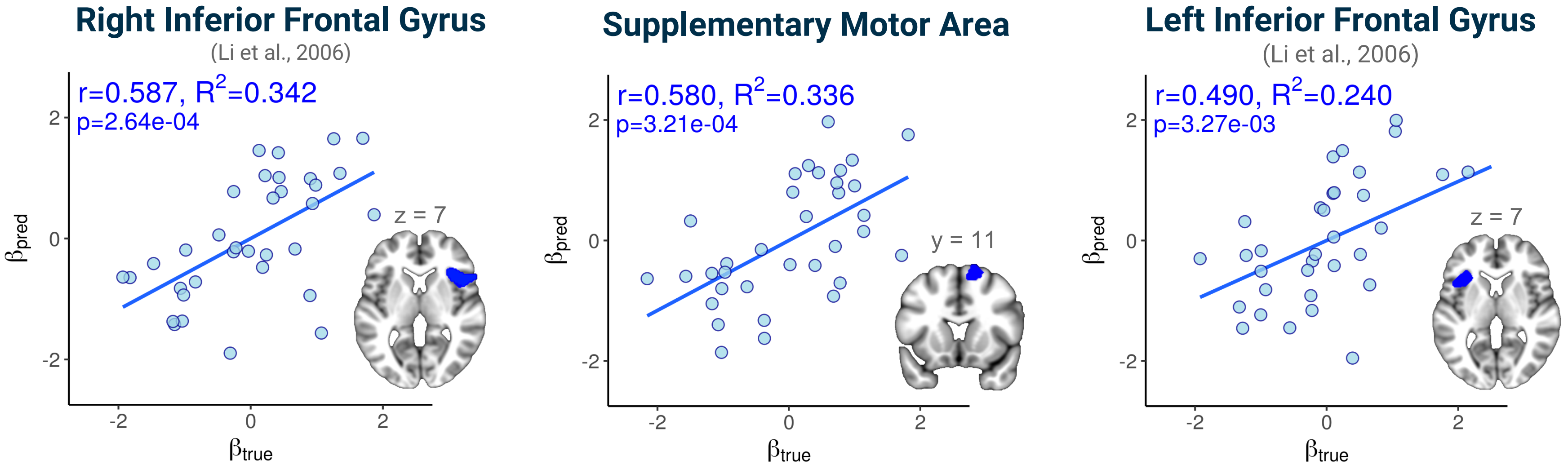
2 Lasso regression with the HbR signals outperformed other models.

Average Mean Squared Error of the Three Predicted Regions Prediction



Result III – *SST Prediction*

3 Three activated areas related to <u>response inhibition</u> in fMRI were predicted by the fNIRS pattern.

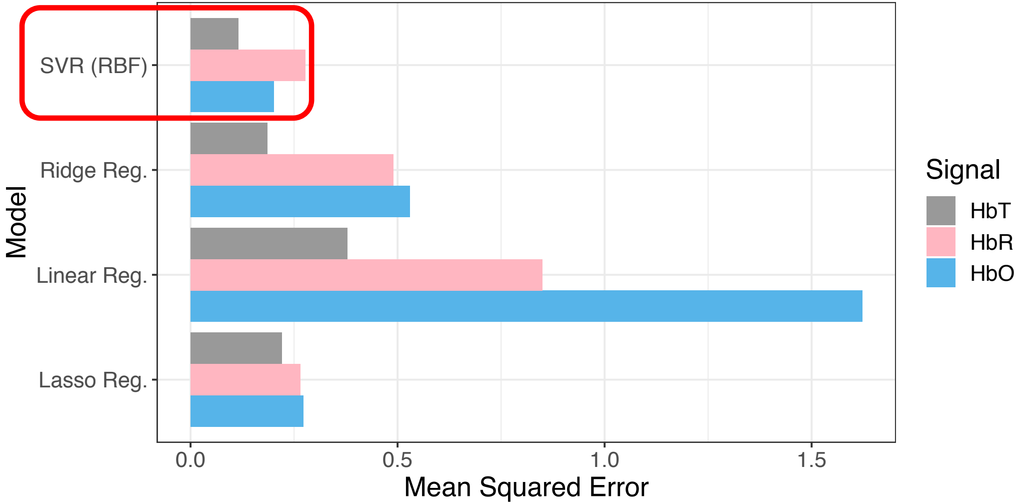


Model: Lasso regression with the HbR fNIRS signal

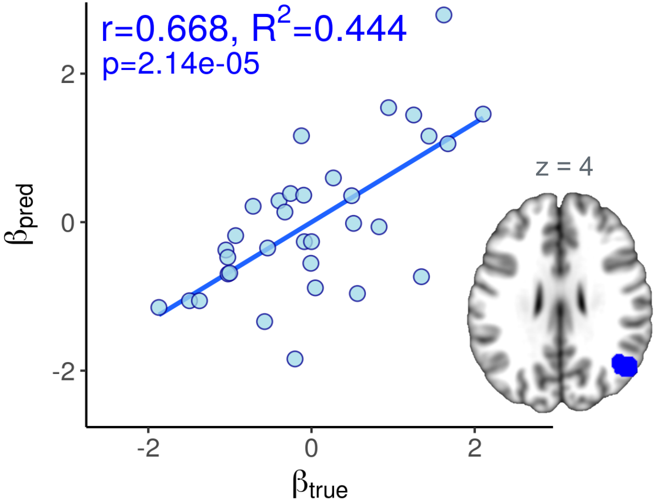
Result IV – *PRL* Model Comparison & Prediction

4 **One activated area related to <u>prediction error</u> in fMRI was predicted by the fNIRS pattern.**

Mean Squared Error of the Inferior Parietal Lobule Prediction



Inferior Parietal Lobule (Jane et al., 2013)



Model: SVR (RBF) with the HbT fNIRS signal

Summary

Summary

- **Scanning environment did not significantly alter task performance.**
- **fNIRS could predict fMRI markers of response inhibition.**
- **fNIRS could predict activation reflecting prediction error during learning.**
- **Our novel prediction pipeline including data augmentation and machine learning models mapped fNIRS into fMRI activation well.**

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Thank you for your listening!