Impulse Response Estimation Methods for Modelling Neural Processing of Continuous Speech

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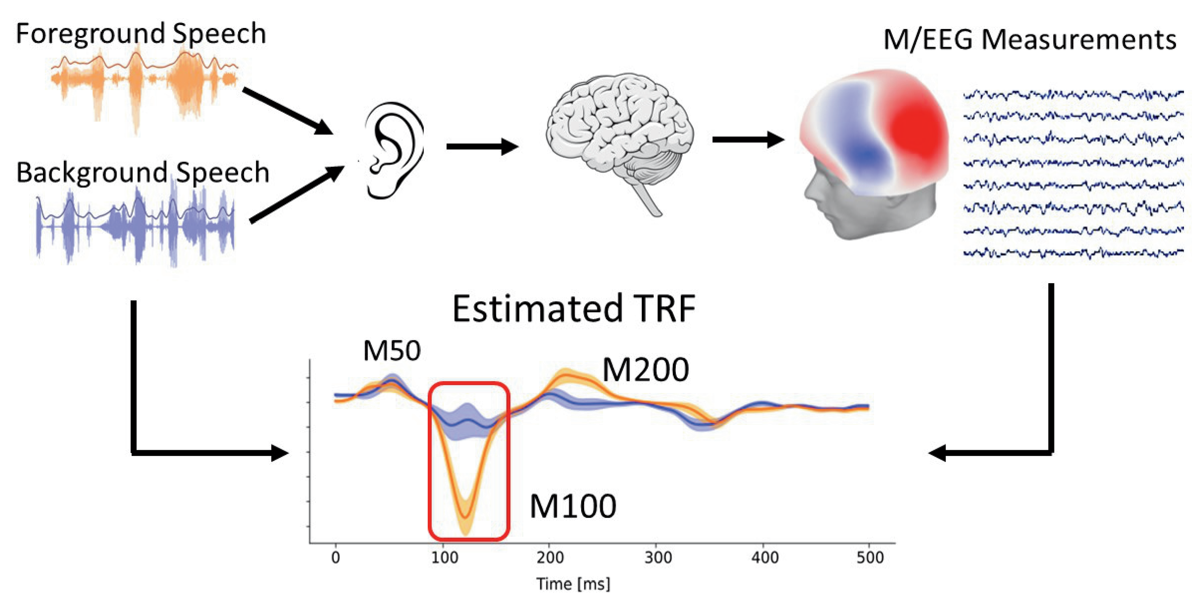
Introduction

- Neural processing of speech involves **time-locked** neural mechanisms that can be detected using **MEG** or **EEG** neuroimaging.
- Linear models called **Temporal Response Functions (TRFs)** are widely used to study the **impulse response** of this neural system
- Accurate estimation of TRF components is essential for subject-specific investigations into speech processing.

The Temporal Response Function (TRF)



- We compare two common methods, **ridge regression** and **boosting**, in terms of their accuracy in estimating TRF components
- We propose novel algorithms based on **Subspace Pursuit (SP)** and **Expectation Maximization (EM)** that utilize prior knowledge to directly estimate TRF components.
- We evaluate performance on simulated and real MEG data

Methods

TRF Model $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{n}$

$\mathbf{y}$: M/EEG response, $\boldsymbol{\beta}$: TRF

$\mathbf{X}$: shifted predictor, $\mathbf{n}$: noise

Ridge Regression

$$\boldsymbol{\beta} = (\mathbf{X}^T\mathbf{X} + \lambda\mathbf{I})^{-1}\mathbf{X}^T\mathbf{y}$$

Boosting

- Greedy coordinate descent
- Incrementally build up the TRF using small changes that minimize the error

Simulation Study

- 30 simulated subjects with TRF component amplitudes, latencies and topographies
- Simulated responses to speech envelopes
- Realistic noise using phase scrambled real MEG responses
- Single-channel, sensor-space and source-space simulations

Performance Metrics

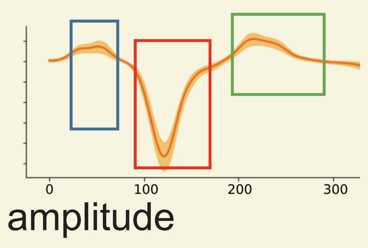
1. Model fit - correlation between actual and predicted signals
2. Correlation between ground truth and predicted TRFs
3. Component amplitude error
4. Component latency error
5. Component topography error (for multichannel TRFs)
6. Spurious TRF activity
7. Missing components

Proposed Algorithms

Subspace Pursuit (SP)

Directly estimate TRF components given component latency windows

$$\mathbf{y} = \sum_j a_j \mathbf{X}\mathbf{c}_j + \mathbf{n}$$



$\mathbf{c}_j$: j[th] TRF component, a_j: amplitude

1. Calculate best component latencies within each window using the residual signal
2. Estimate amplitudes using Least Squares
3. Calculate residual signal
4. Repeat 1-3 until convergence

Expectation Maximization SP (EM-SP)

Extends SP for multichannel TRFs

Directly estimates component amplitudes, latencies and spatial topographies

$$\mathbf{Y} = \sum_j \mathbf{z}_j \left(\mathbf{X}\mathbf{c}_j\right)^T + \mathbf{N}$$

$\mathbf{Y}$: multichannel M/EEG response

$\mathbf{z}_j$: spatial topography of j[th] component

1. E-step: Estimate spatial topographies $\mathbf{z}_j$
2. M-step: Estimate prior parameters
3. M-step: Estimate latencies using SP
4. Repeat 1-3 until convergence

Real Data

- Prevoiusly published MEG dataset (Presacco et. al. 2016)
- 40 subjects listening to foreground and background speech
- Sensor and source space TRFs were estimated
- Model fit correlation between actual and predicted response

Results - Simulation

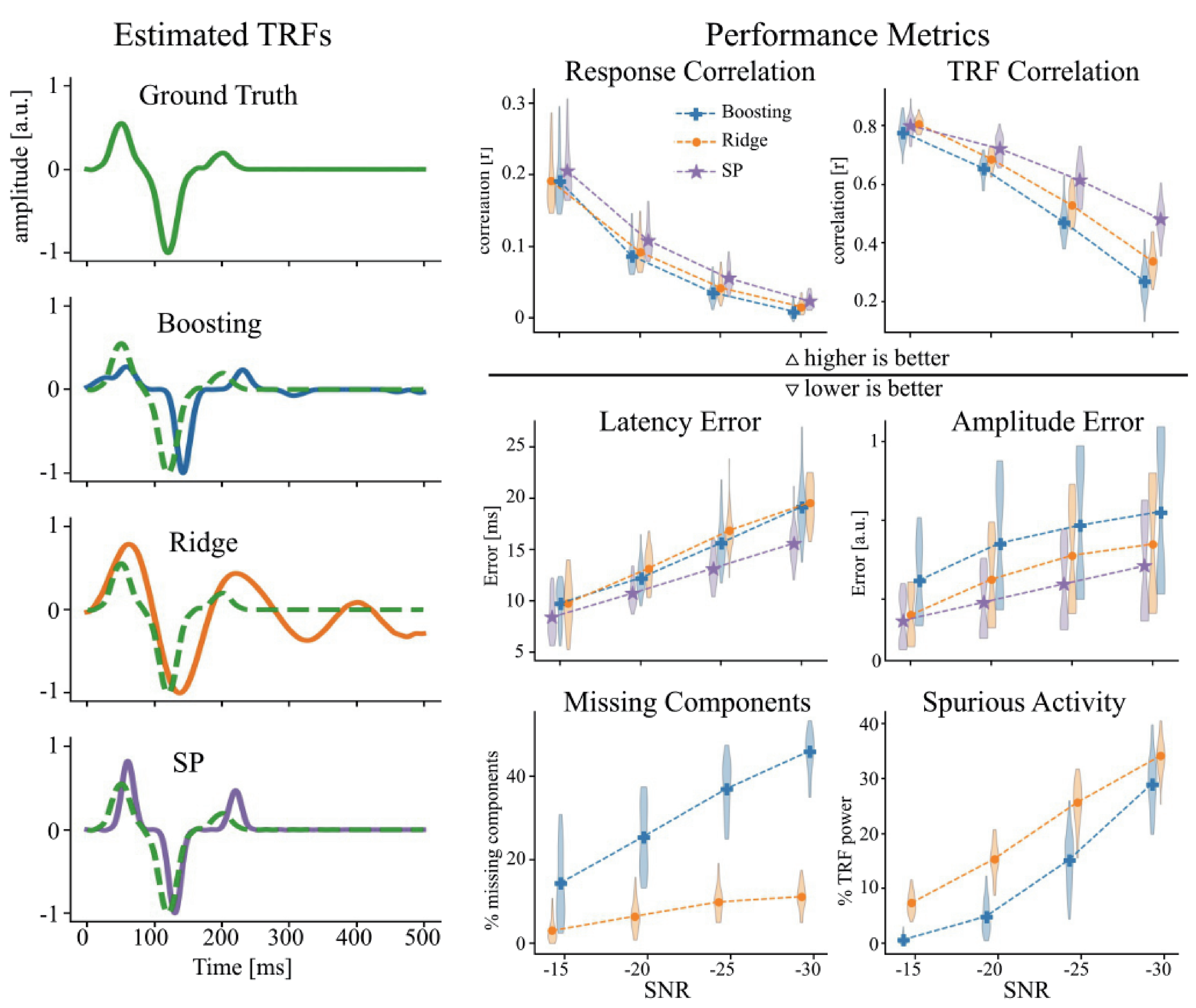
Single Channel TRFs

- All methods are comparable at high SNR
- SP outperforms ridge and boosting at low SNR
- Ridge has more spurious activity
- Boosting has more missing components

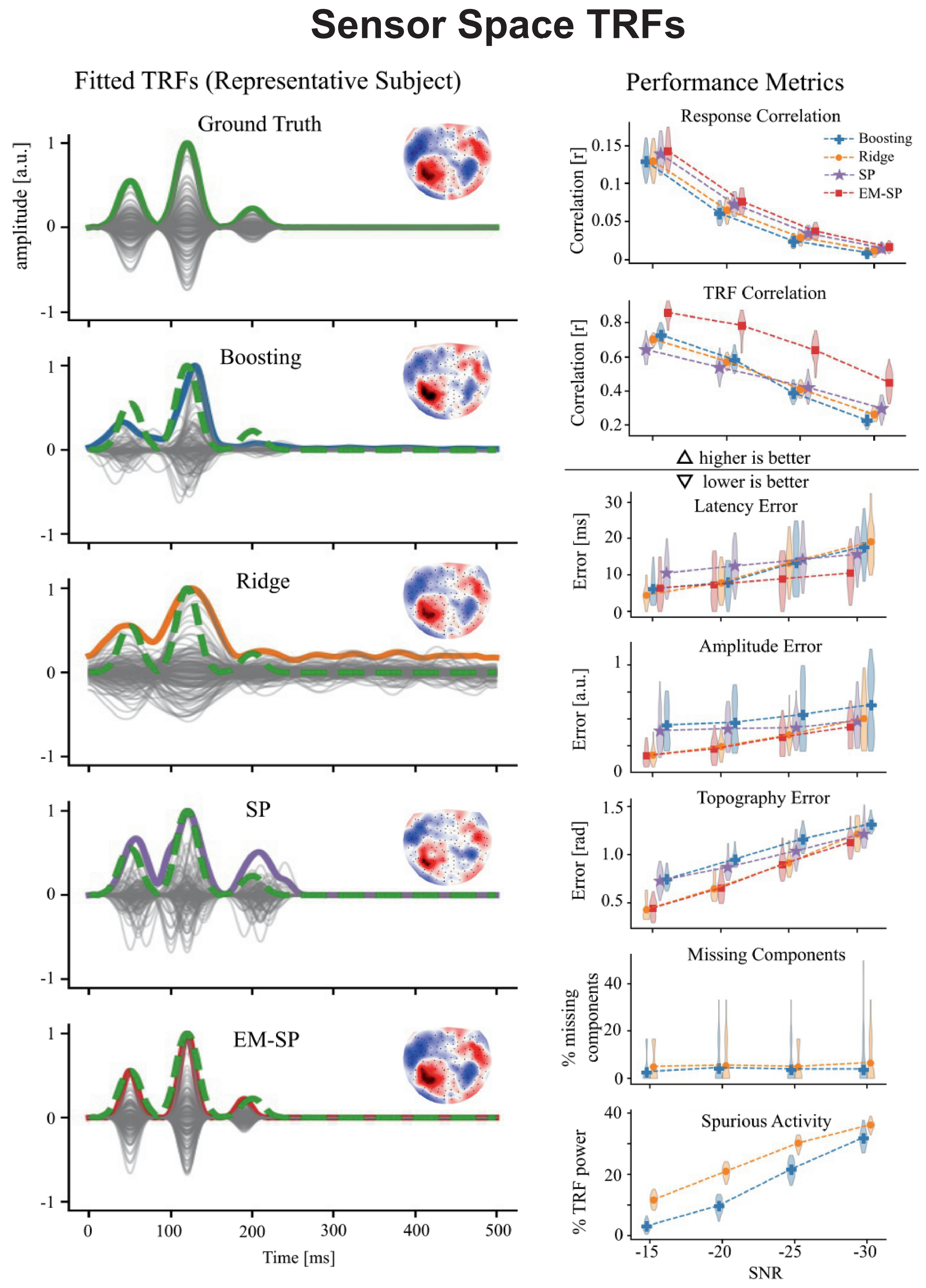
Sensor and Source Space TRFs

- All methods are comparable at high SNR
- EM-SP outperforms ridge and boosting, especially at low SNR
- SP alone does not perform well
- Ridge has more spurious activity
- Boosting has sparser topographies

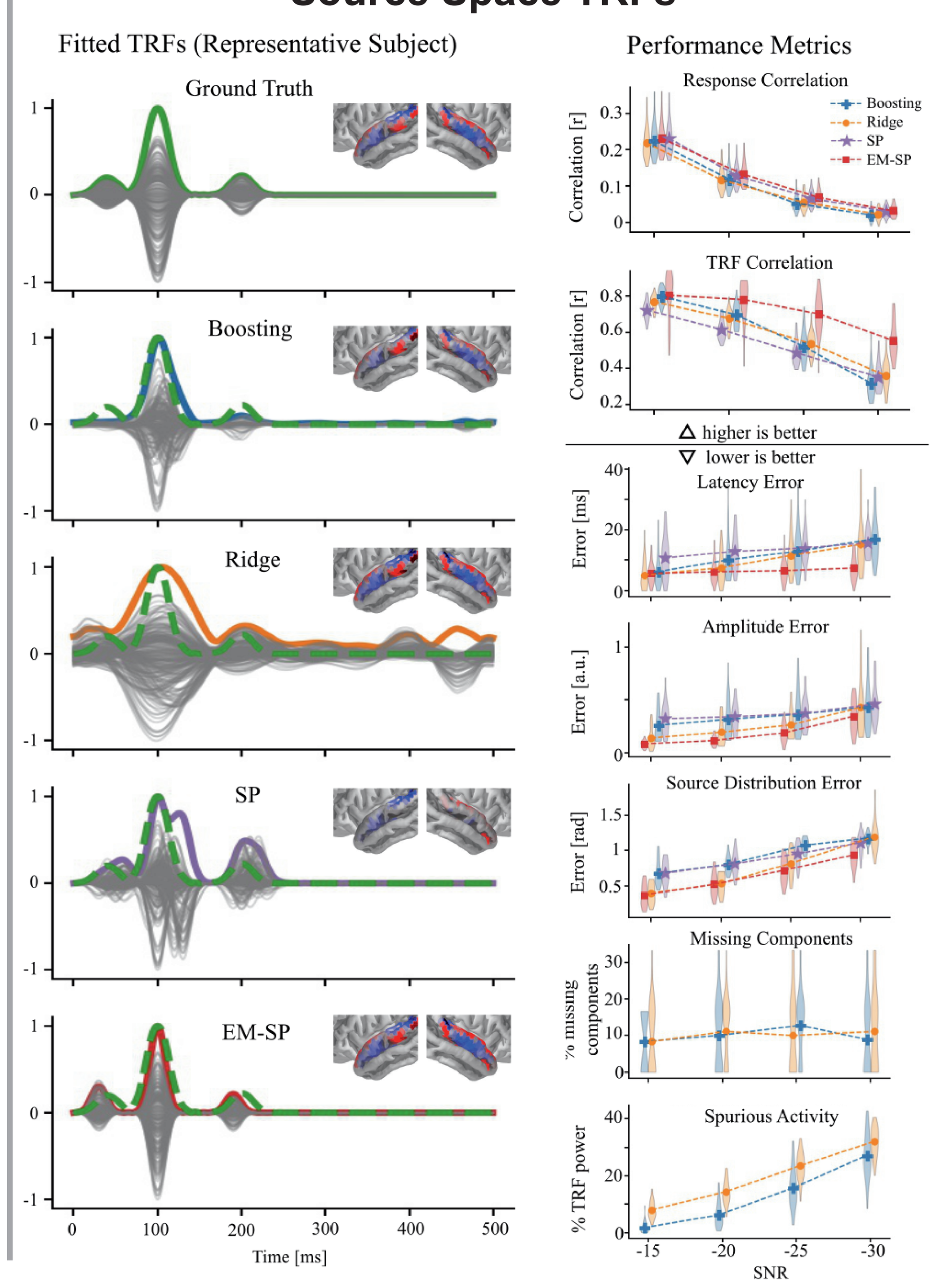
Single Channel TRFs



Sensor Space TRFs



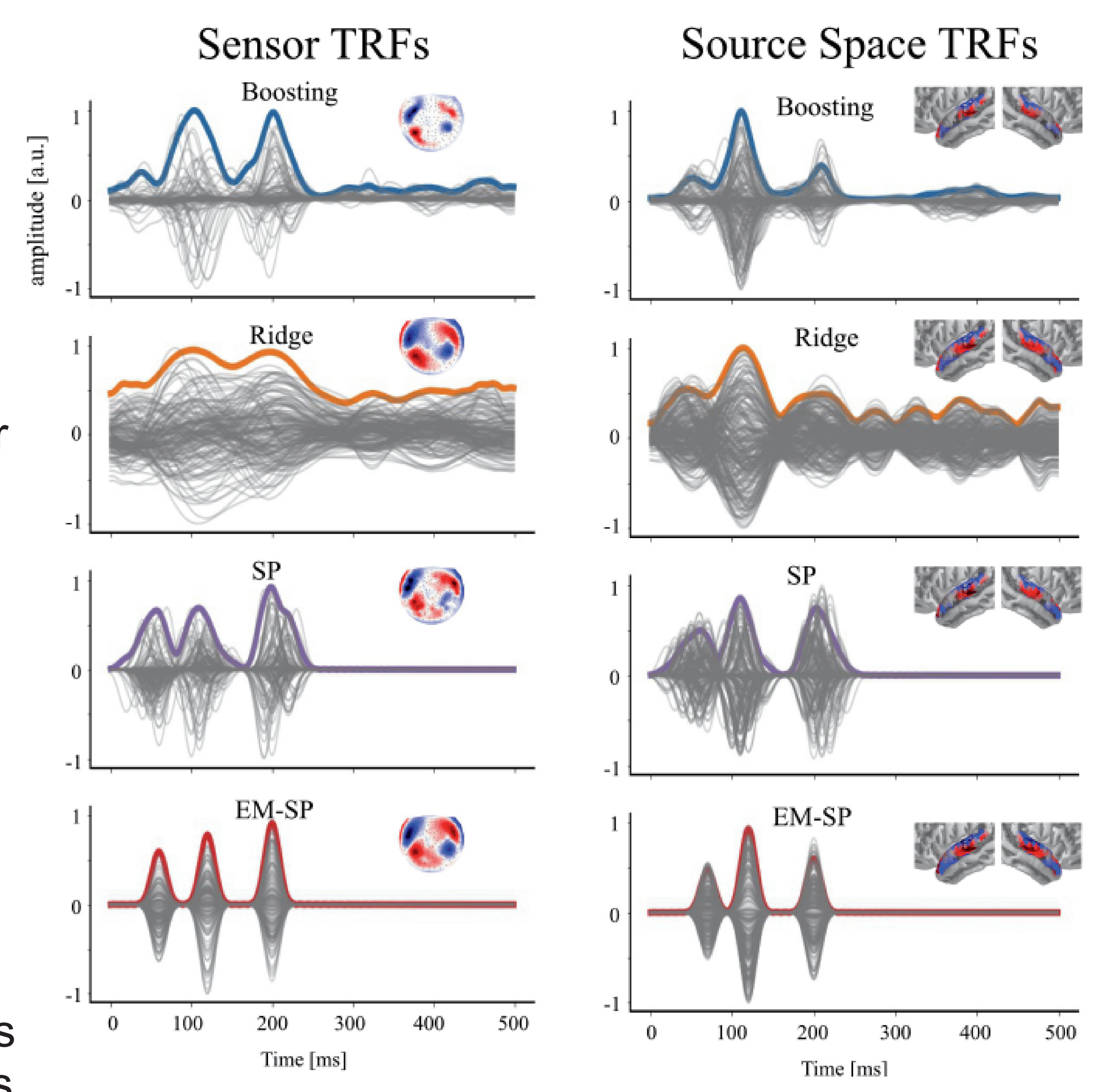
Source Space TRFs

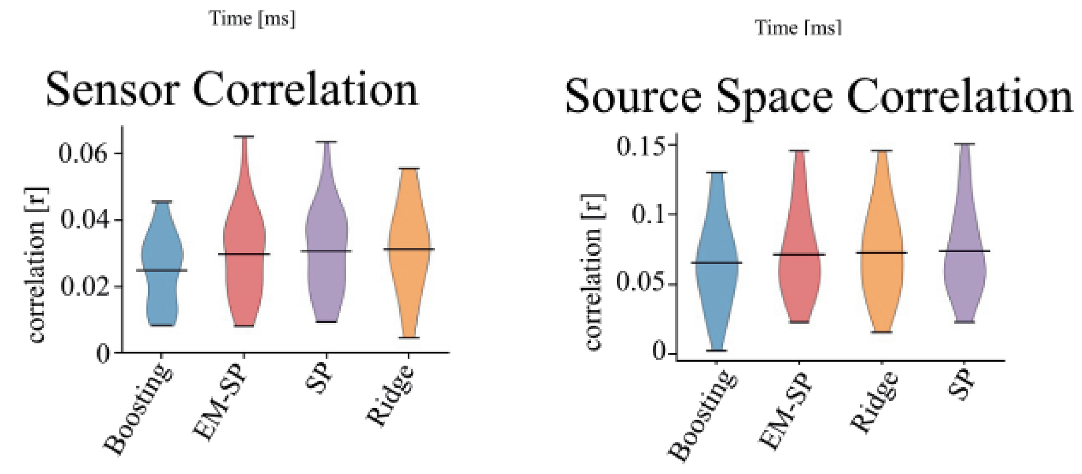


Results - Real Data

- Similar TRF components estimated by all algorithms
- Ridge has more spurious activity
- Boosting has sparser topographies
- Source space TRFs are much cleaner

- **Model fit correlations** are similar across methods
- EM-SP does not outperform the others like in the simulations
- Boosting has a slightly lower correlation than other algorithms





Conclusions

- SP and EM-SP are able to detect TRF components in both simulations and real data
- SP outperforms ridge and boosting in single channel simulations
- EM-SP outperforms ridge and boosting in multi channel simulations
- EM-SP did not outperform the others on real data, perhaps due to high amounts of individual variability in TRF components, or incorrect TRF latency windows
- Ridge and boosting are comparable for most metrics
- Ridge has more spurious activity, while boosting may miss some TRF components

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This work is available as a preprint

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