

Multilinear Subspace Regression: An Orthogonal Tensor Decomposition Approach

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LABSP: <http://www.bsp.brain.riken.jp/>

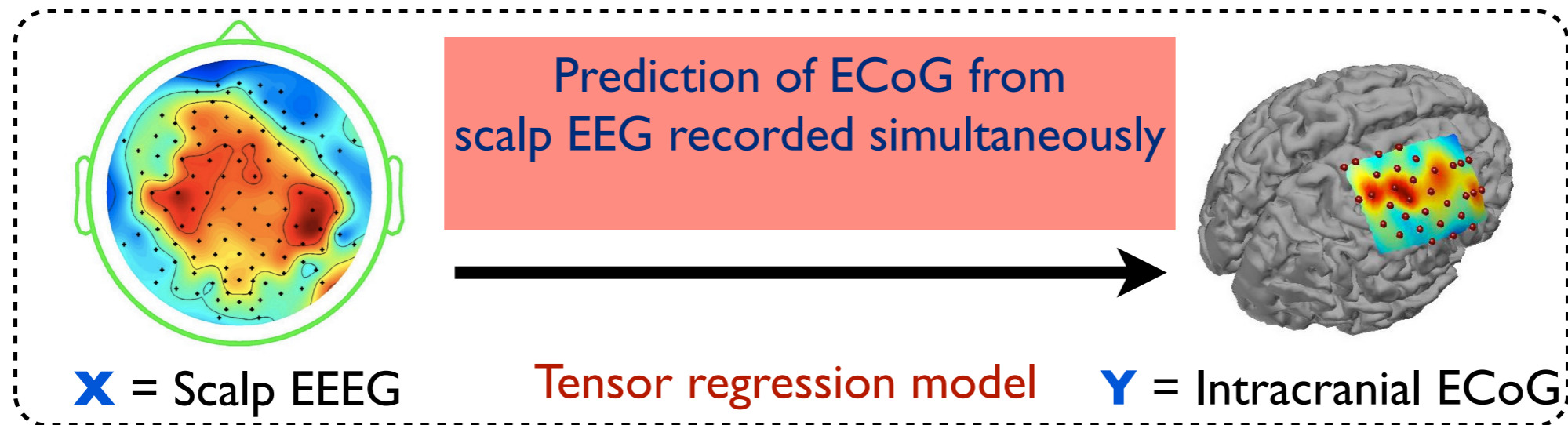


Multilinear regression and applications

► **Tensor** representation of multidimensional data

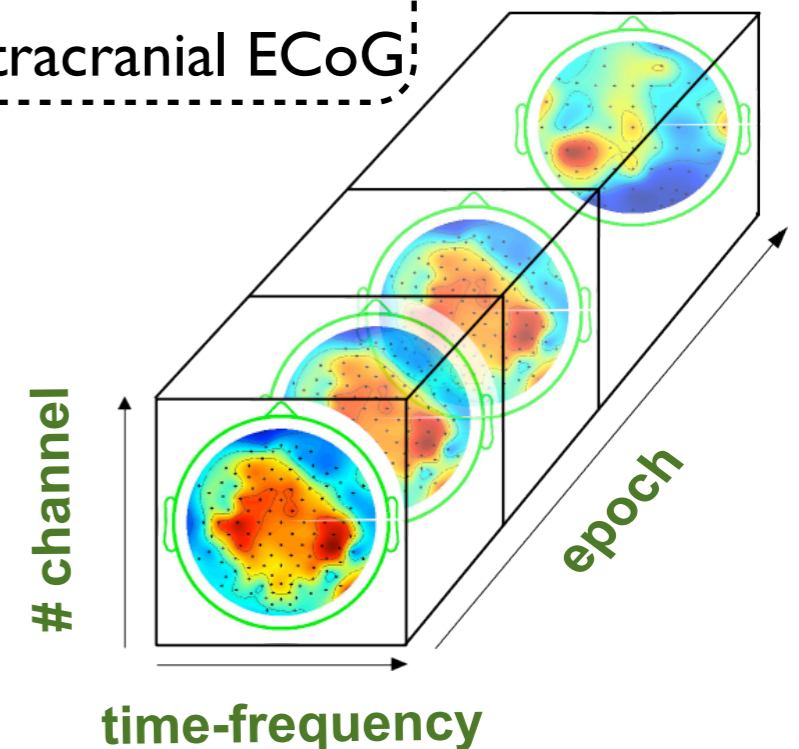
- EEG, ECoG (spatial, temporal, frequency, epoch,...)
- Physical meaning - ease of interpretation

► From multivariate to multi-way array processes - partial least squares (PLS)



► Standard PLS applied on **matricization** of both X and Y

- Small sample size problem
- Overfitting problem (high dimension of subspace basis)
- Lack of physical interpretation for loadings



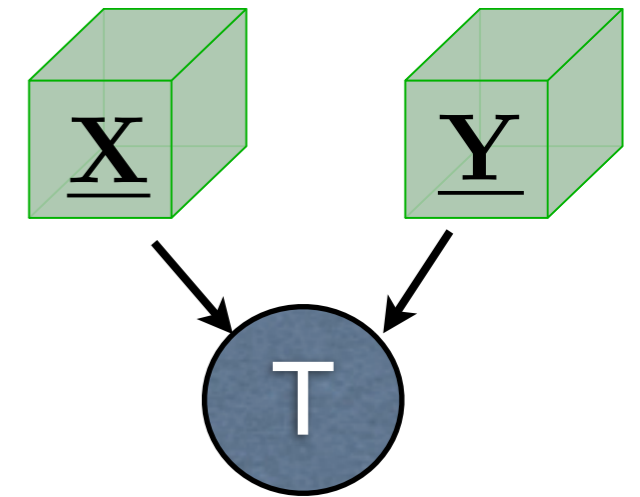
Proposed approach

Objective function

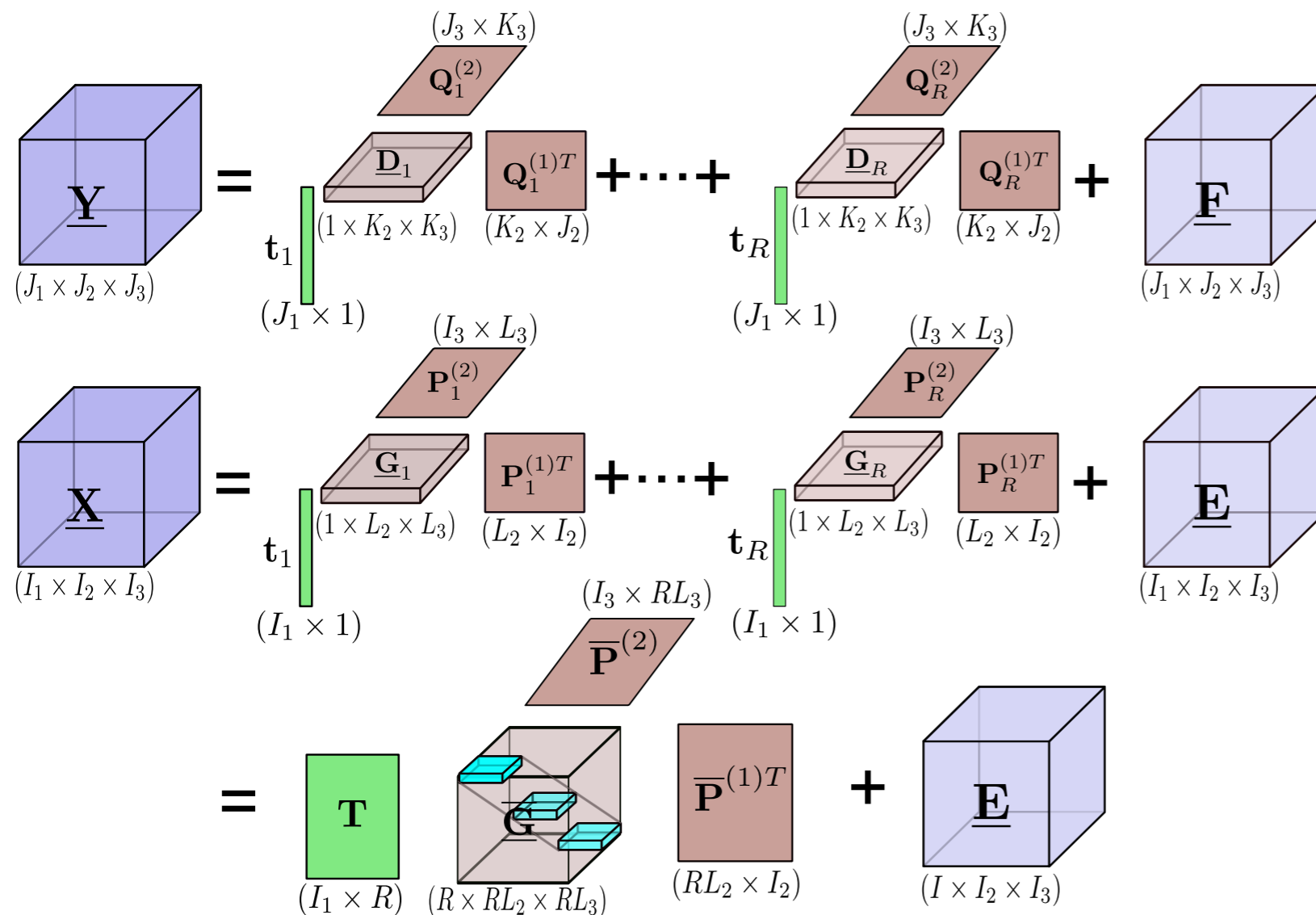
$$\min_{\{\mathbf{P}^{(n)}, \mathbf{Q}^{(m)}\}} \left\| \underline{\mathbf{X}} - \llbracket \underline{\mathbf{G}}; \mathbf{t}, \mathbf{P}^{(1)}, \dots, \mathbf{P}^{(N-1)} \rrbracket \right\|^2 + \left\| \underline{\mathbf{Y}} - \llbracket \underline{\mathbf{D}}; \mathbf{t}, \mathbf{Q}^{(1)}, \dots, \mathbf{Q}^{(M-1)} \rrbracket \right\|^2$$

$$\text{s. t. } \{\mathbf{P}^{(n)T} \mathbf{P}^{(n)}\} = \mathbf{I}_{L_{n+1}}, \quad \{\mathbf{Q}^{(m)T} \mathbf{Q}^{(m)}\} = \mathbf{I}_{K_{m+1}},$$

Brain data Behavior data



Latent variable



Raw Data Latent variables Loadings Residuals

Extension of PLS to higher-order tensor data - HOPLS

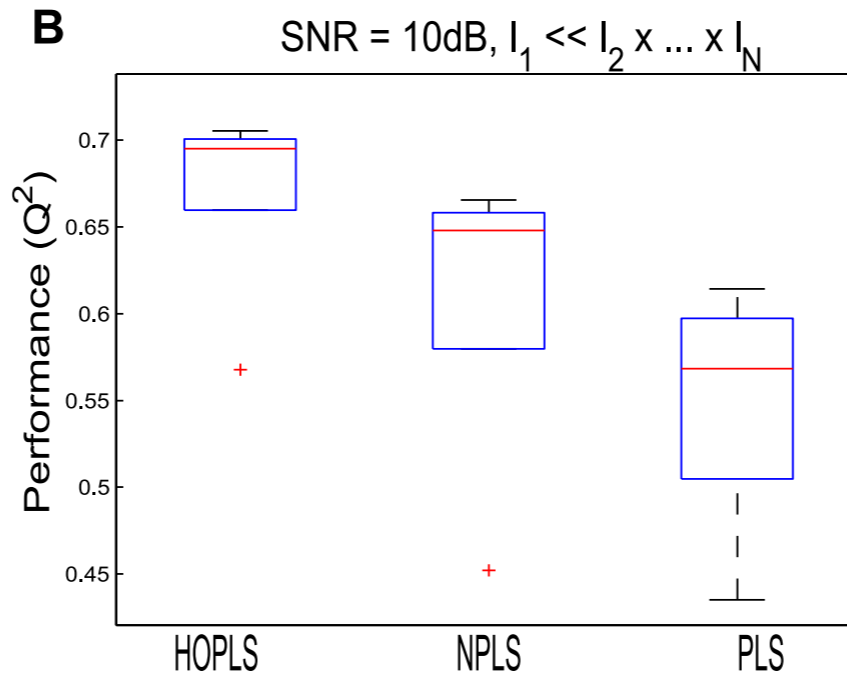
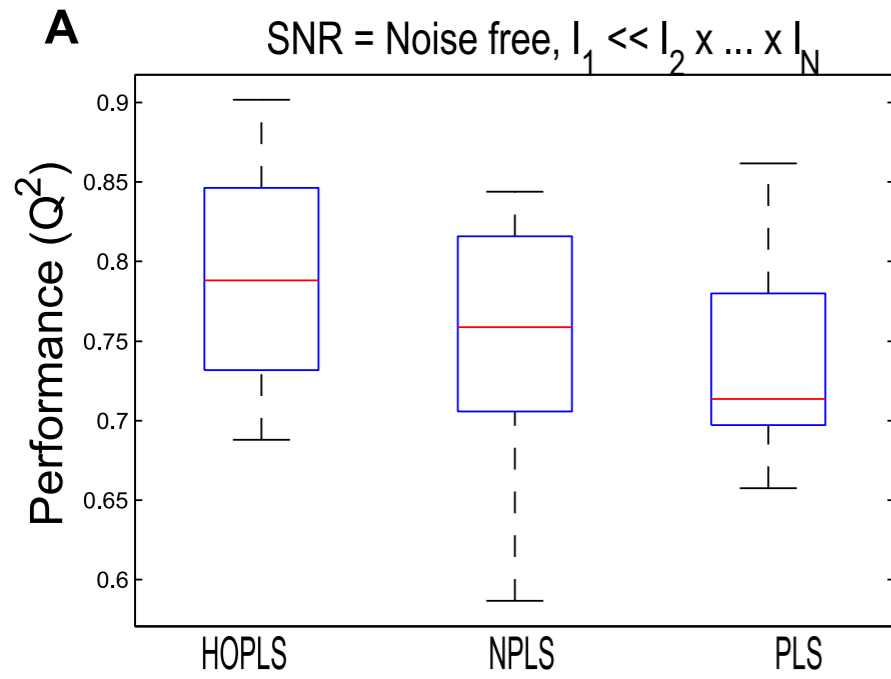
- Goal: to predict a tensor \mathbf{Y} from a tensor \mathbf{X}
- Approach: to extract the common latent variables

Properties:

- Flexible multilinear regression framework
- Projection on tensor subspace basis
- Efficient optimization algorithm using HOOI on the n -mode cross-covariance tensor

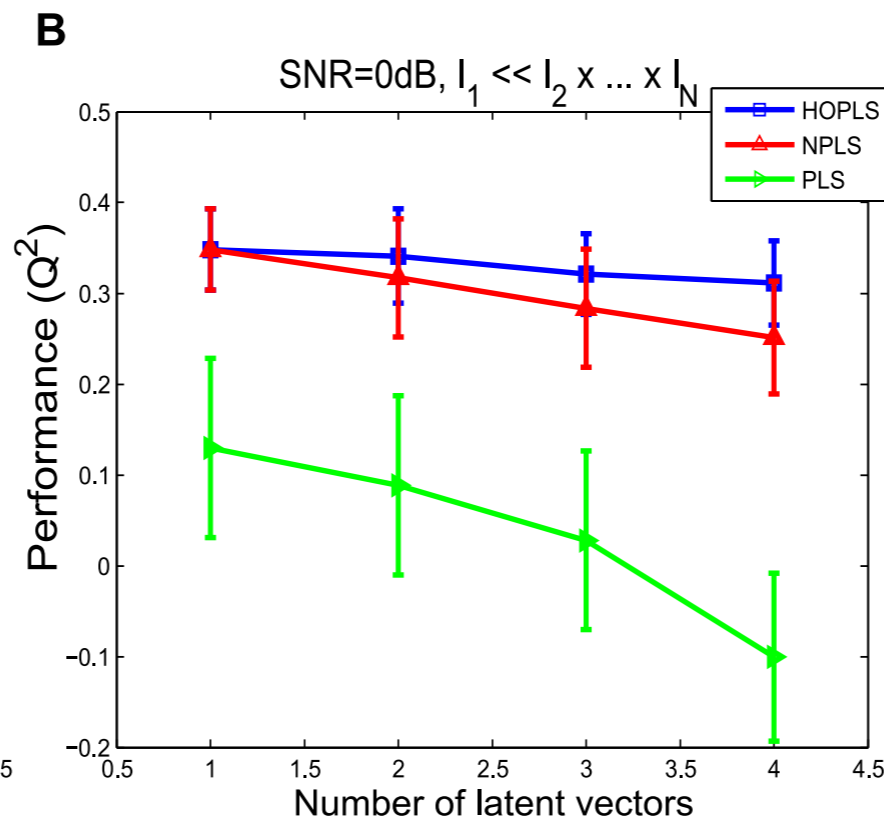
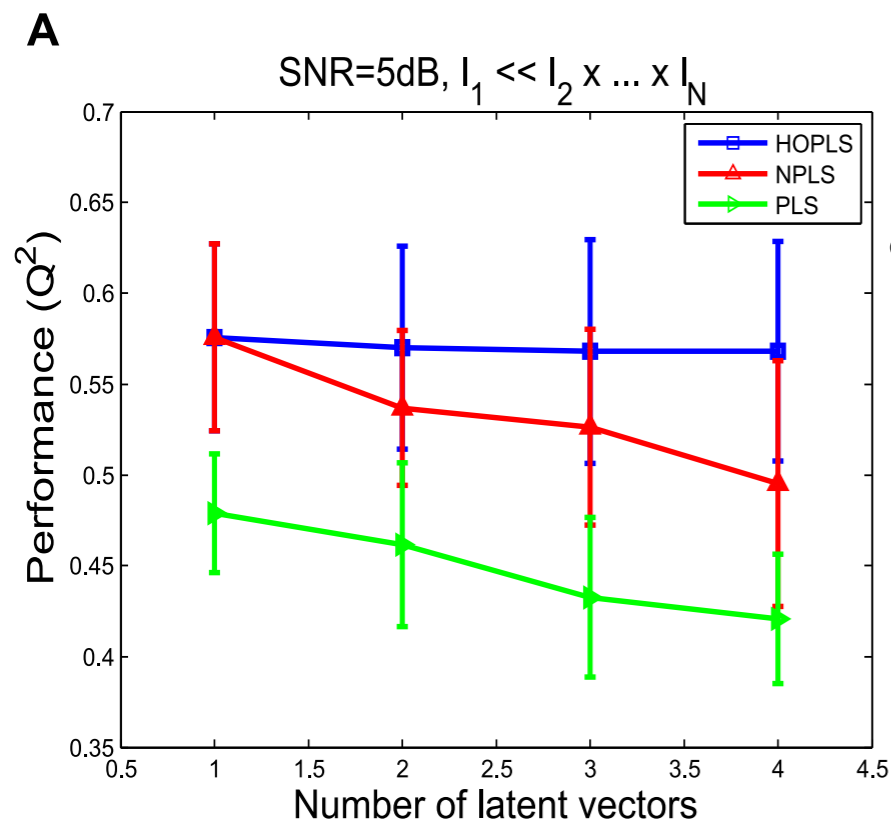
Key advantages

Small sample size



HOPLS: better prediction performance and enhanced robustness to noise

Robustness against overfitting and noise



Stability of the performance of HOPLS, NPLS and PLS for a varying number of latent vectors under different noise conditions

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