Whole-brain dynamical modeling for classification of Parkinson's disease

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Introduction

1. Simulated whole-brain connectomes demonstrate an enhanced inter-individual variability depending on data processing and modeling approach.
2. We thus hypothesized that **MRI data processing** can impact the application of whole-brain models to subject classification and affect their performance.
3. We also introduced **a novel validation approach** for whole-brain dynamical models to enhance the classification performance.
4. To this end, we investigate how empirical and simulated whole-brain connectome-derived features can be utilized to classify patients with Parkinson's disease against healthy controls in light of varying data processing and model validation.

Methods: Whole-brain dynamical modeling and classification using machine learning

❖**Participants:** **51** (30 males) **healthy controls** and **65** (45 males) **patients** with Parkinson's disease
- MRI acquisition: T1-weighted image, resting-state fMRI (rsfMRI), and diffusion-weighted images (DWI) with 64 directions
- MRI processing: Extracting blood oxygenation level-dependent (BOLD) signals from rsfMRI and reconstructing whole-brain tractography with 10M streamlines using DWI

MRI pipeline | Jung et al. (2023)

❖**Whole-brain model:** Convolution-based two-population model (Jansen-Rit type[1,2]) for electrical signals + Balloon-Windkessel model[3,4] for BOLD signals

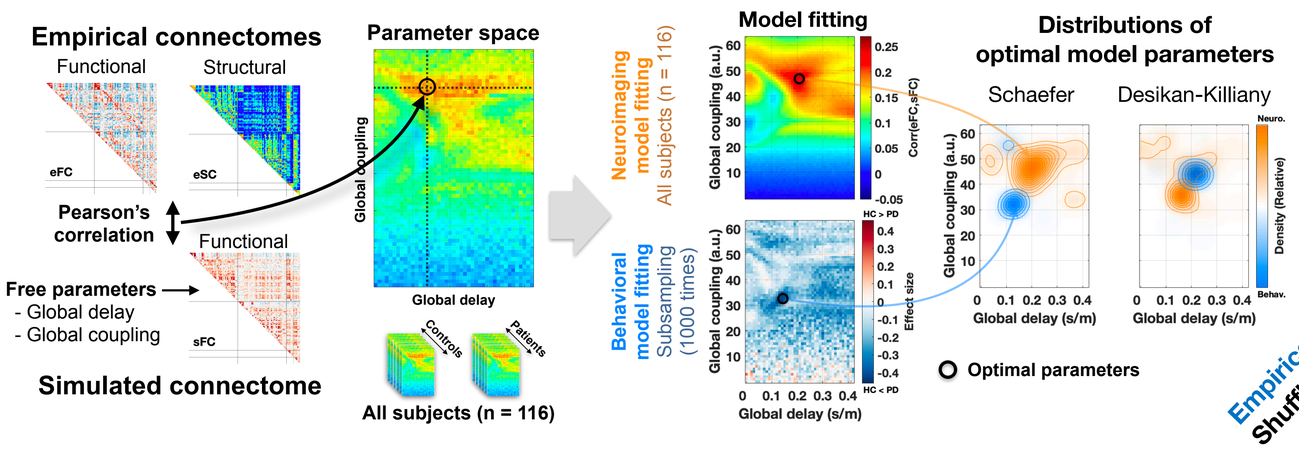
❖**Experimental conditions:** **Four temporal filters (NF, BF, LF, and HF)** for empirical and simulated BOLD signals + **Two parcellation schemes** (**Schaefer 100 Parcels** and **Desikan-Killiany**)
- **NF:** no filtering, **BF:** broad frequency band [0.01,0.1] Hz, **LF:** low frequency band [0.01,0.05] Hz, **HF:** high frequency band [0.05,0.1] Hz

✓ **Neuroimaging model fitting:** Search for the optimal model parameters corresponding to **the maximal similarity** between empirical and simulated connectomes
✓ **Behavioral model fitting (a novel approach):** Search for the optimal model parameters corresponding to **the maximal difference** between groups of controls and patients

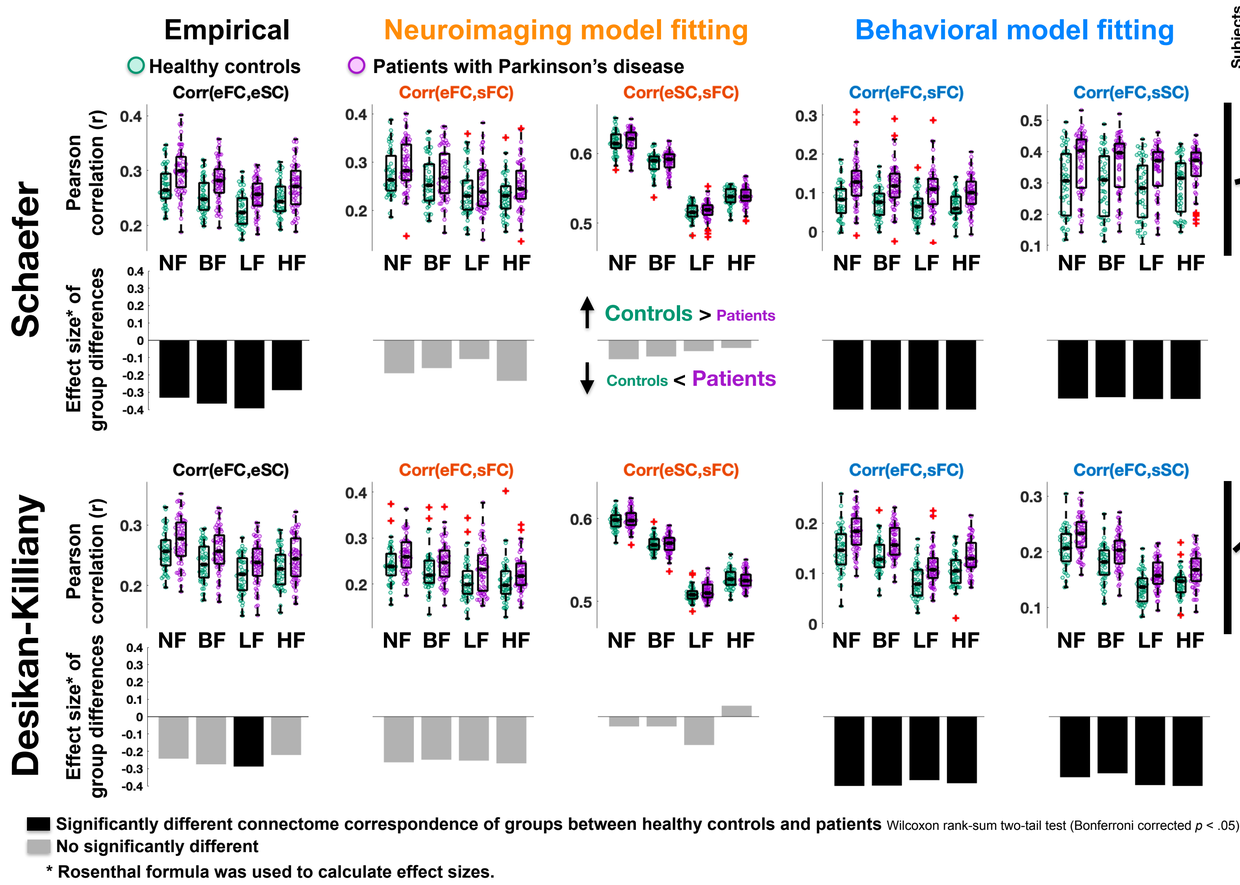
❖**Machine learning:** A **regularized** (**LASSO**: the least absolute shrinkage and selection operator) **logistic regression** using a **cross-validated model fitting and confound regression**[5]

Results: Data processing and model fitting for effective classification of Parkinson's disease

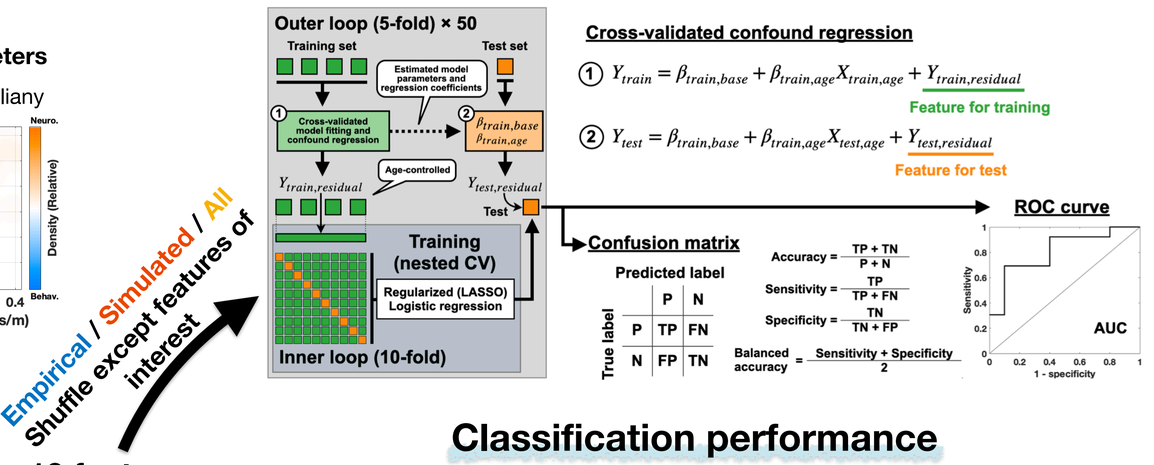
1. Empirical and simulated **connectomes** for model fitting



2. Connectome relationships as **features** for classification



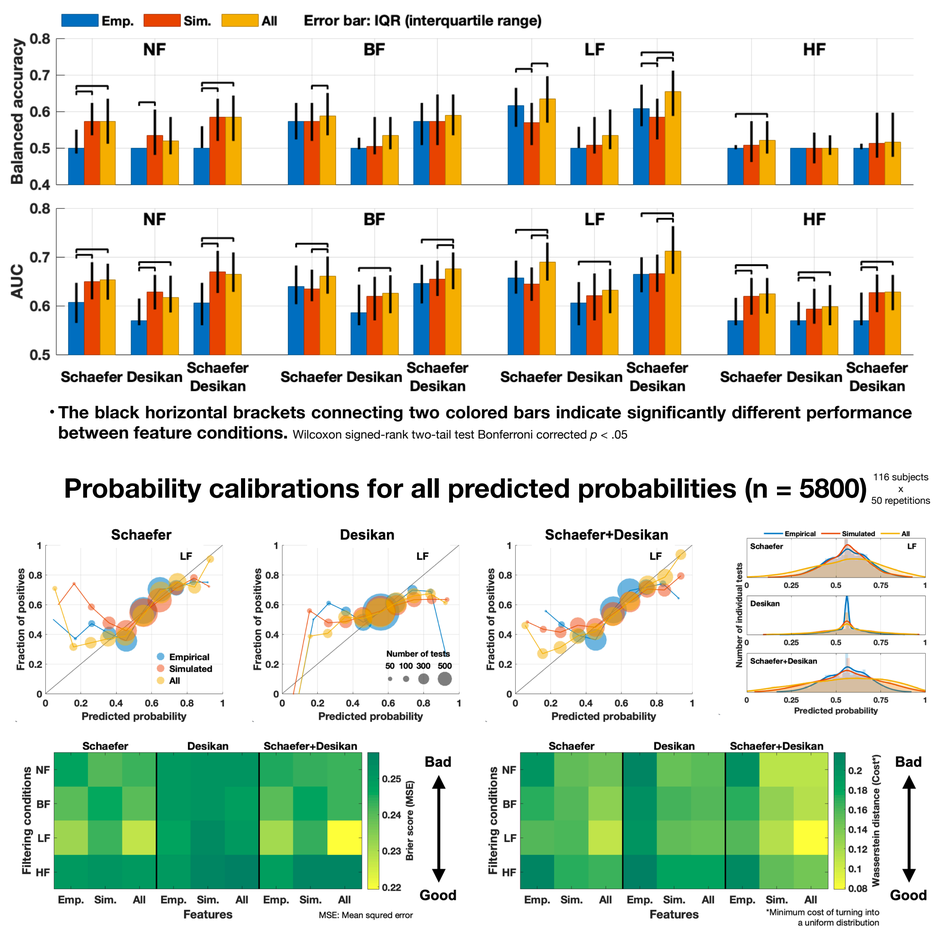
3. **Training** using a cross-validated confound regression



Empirical / Simulated / All
Shuffle except features of interest

10 features
Subjects
Schaefer
Desikan
5 features
5 features

Classification performance



Conclusion

- The novel **behavioral model fitting paradigm** results in an **enhanced differentiation** of disease and control groups and **improved classification** of Parkinsonian patients by machine-learning approaches.
- The **low-frequency [0.01,0.05] Hz** band-pass filtering of BOLD signals can have a beneficial effect on the prediction performance of Parkinson's disease.
- The prediction performance can further be improved when **multiple brain parcellation schemes** were utilized.
- With the current approach, we suggest further **applications of whole-brain dynamical modeling** for cognitive or clinical measures and their interpretations.

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