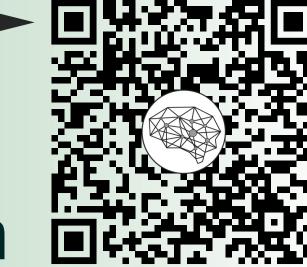
PyRASA - Spectral parameterization in Python based on IRASA

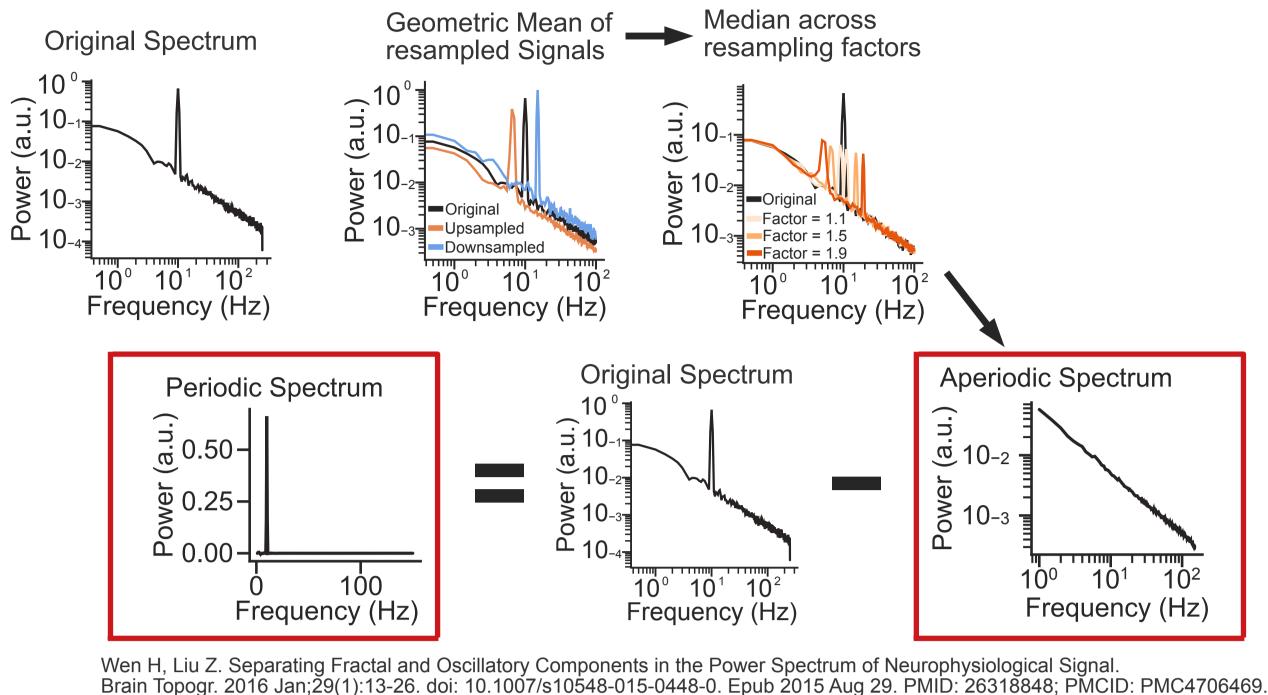




Fabian Schmidt¹, Thomas Hartmann¹ & Nathan Weisz¹²

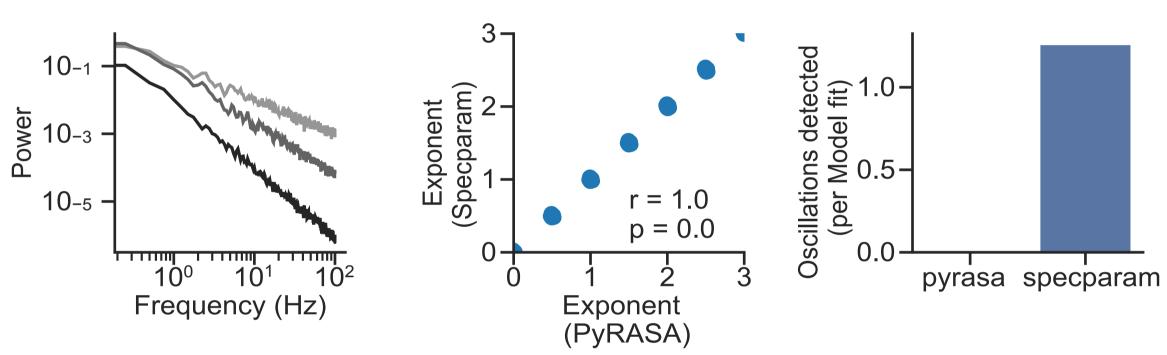
1. Paris-Lodron-University of Salzburg, Department of Psychology, Centre for Cognitive Neuroscience, Salzburg, Austria 2. Neuroscience Institute, Christian Doppler Univsersity Hospital, Paracelsus Medical University, Salzburg, Austria

Separating periodic from aperiodic components using the IRASA algorithm

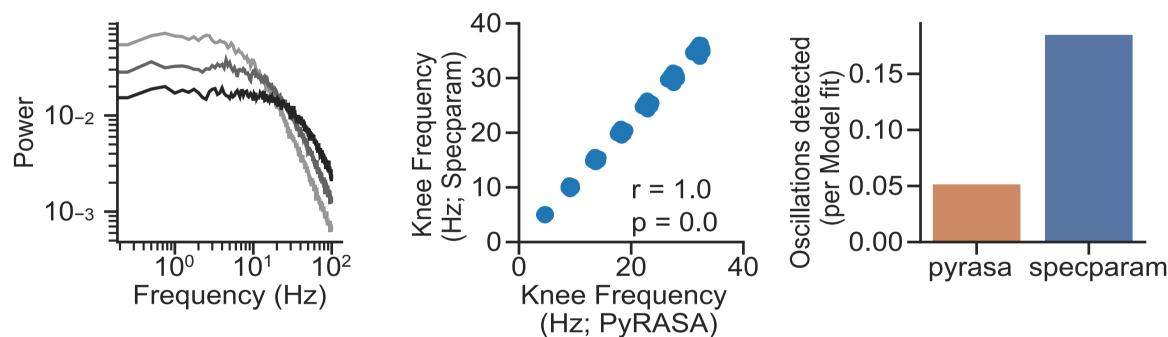


PyRASA accurately detects parameter specific changes in simulated power spectra

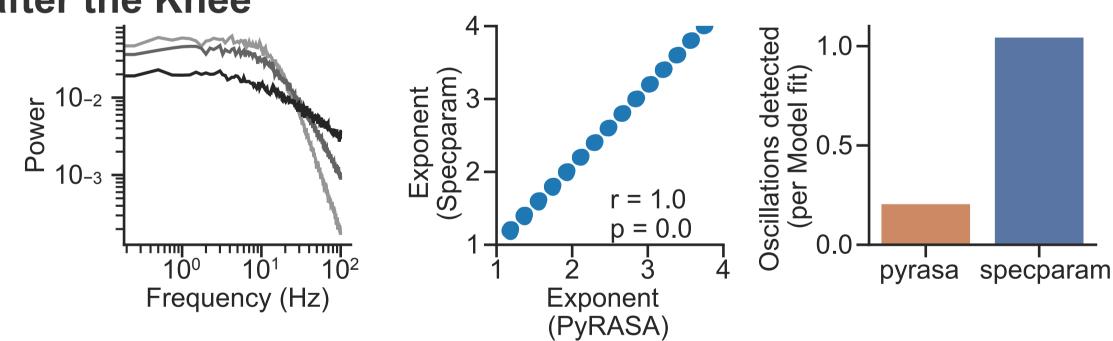
Challenge #1: Detect variations in the Spectral Exponent



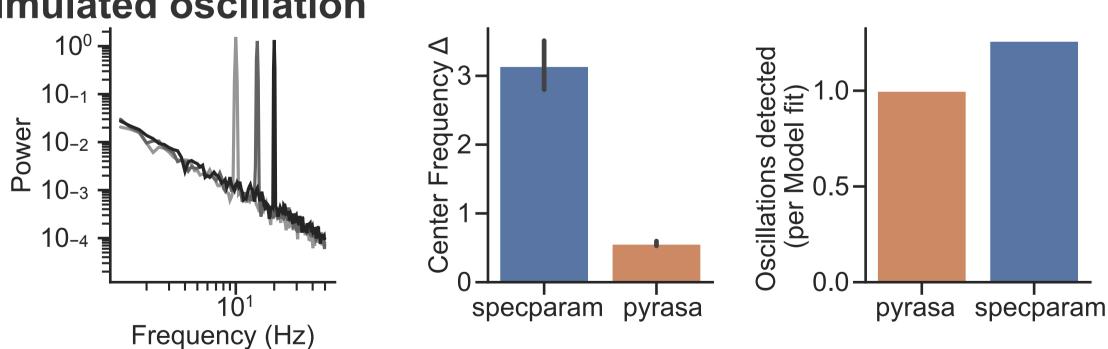
Challenge #2: Detect variations in the Knee Frequency



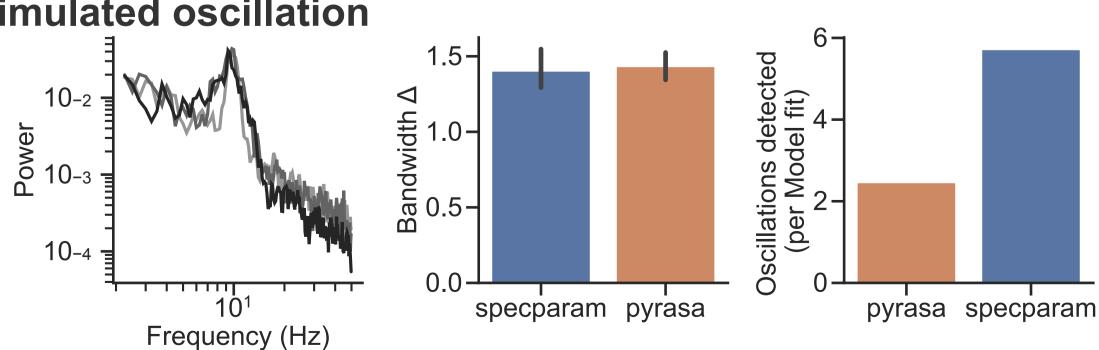
Challenge #3: Detect variations in the Spectral Exponent after the Knee



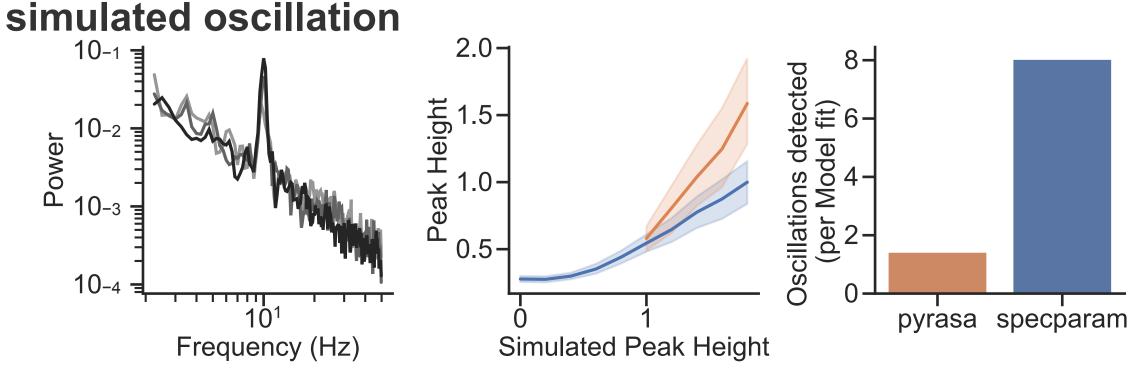
Challenge #4: Detect variations in the Center Frequency of a simulated oscillation



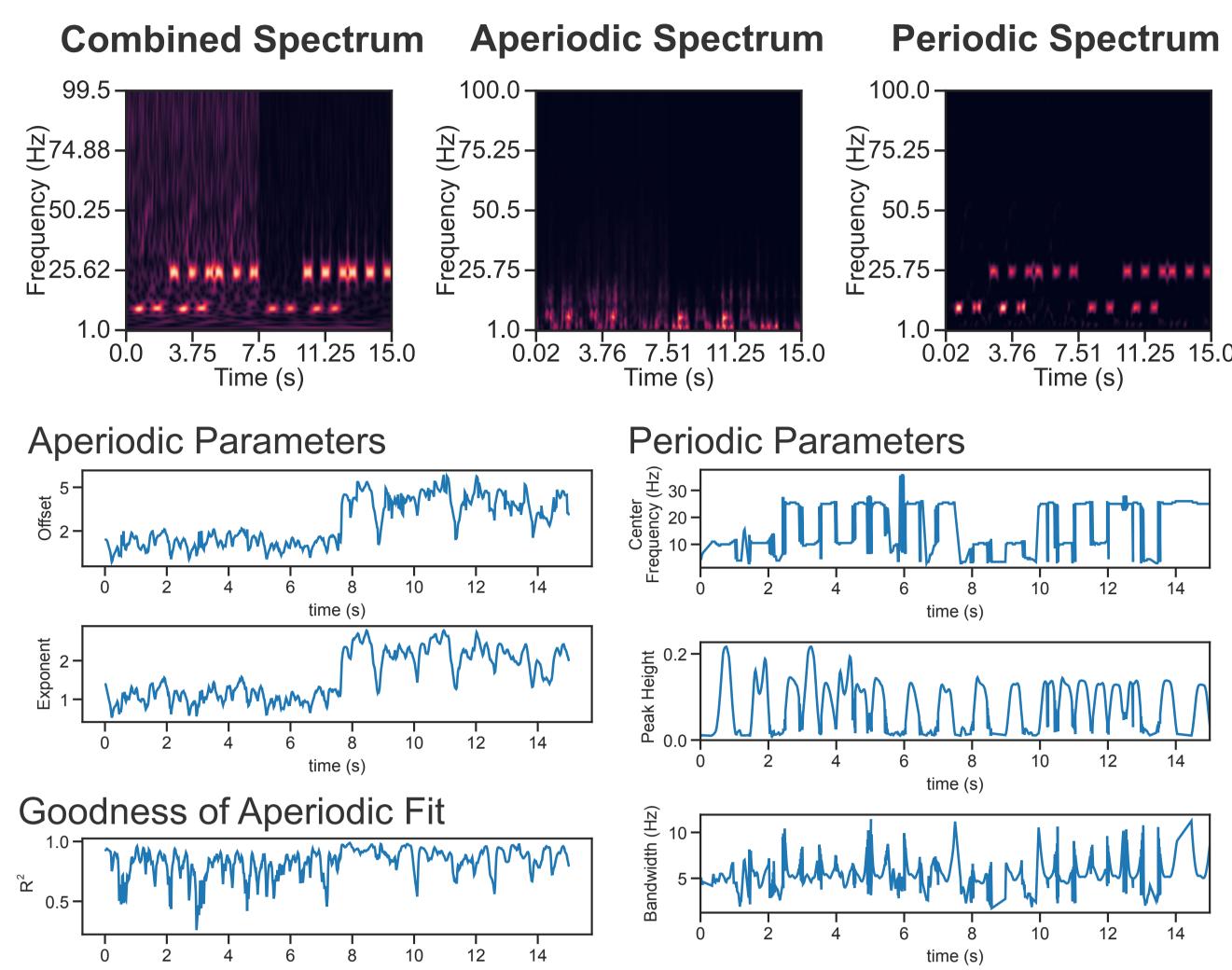
Challenge #5: Detect variations in the Bandwidth of a simulated oscillation



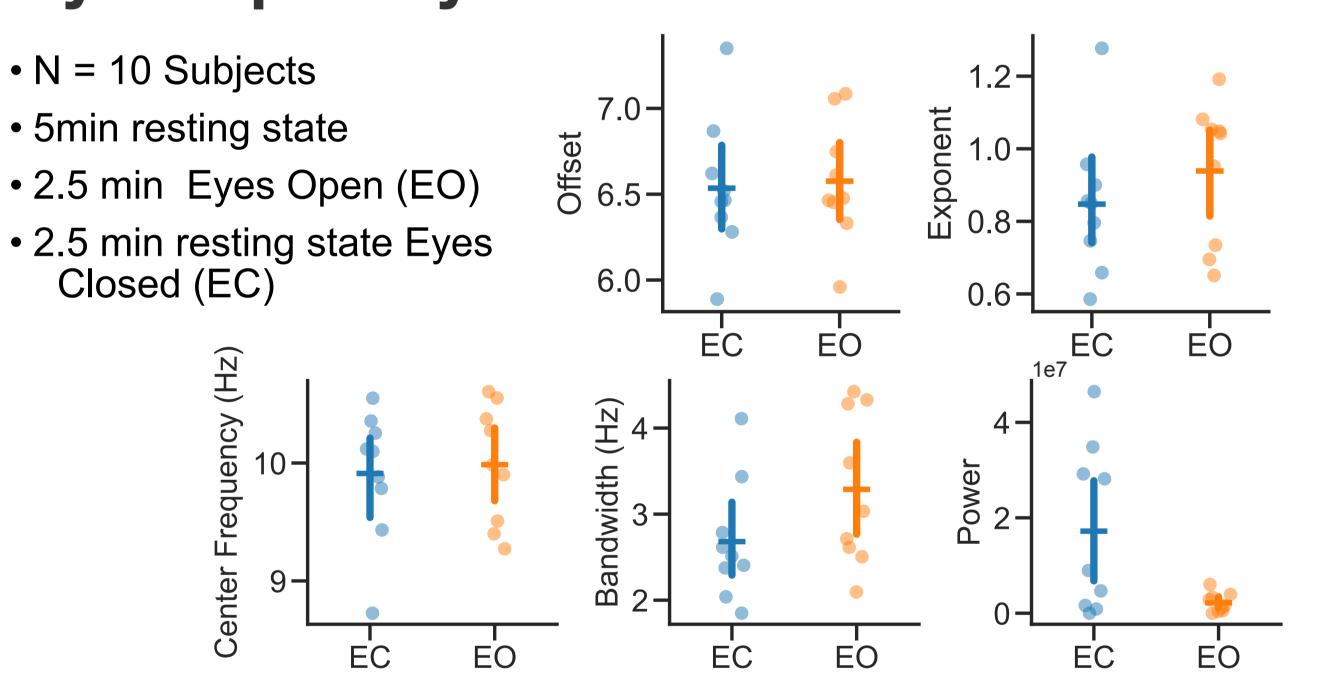
Challenge #6: Detect variations in the Amplitude of a



Time resolved spectral parametrization using PyRASA

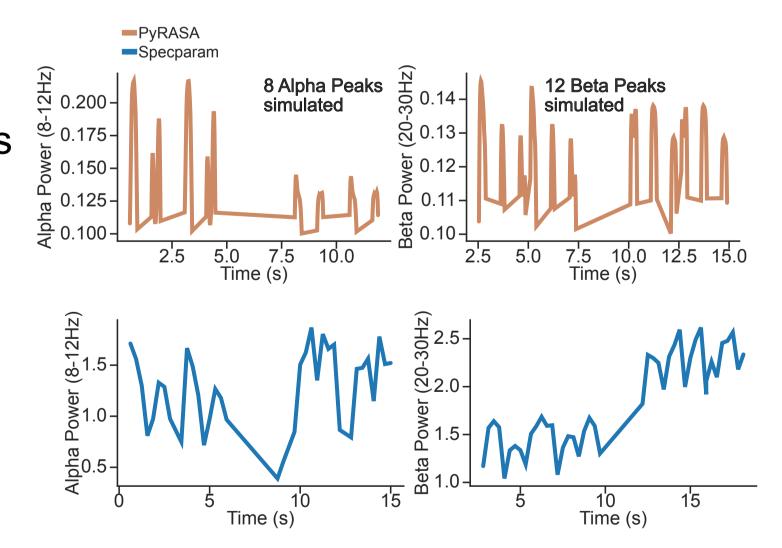


Sanity-Checks on real EEG data **Eyes-Open/Eyes Closed**



Benefits of PyRASA

- Decouples the analysis of periodic and aperiodic parameters
- More stable in detecting oscillations in data with a low SNR
- Less parameters to specify during model fitting
- Aperiodic model comparison using information criteria (e.g. BIC/AIC)
- Fitting functions that include two varying exponents



PyRASA works not so well, when...

- You have broad and very large peaks in your spectra. In these situations the exponent estimation is biased making specparam is the better choice
- You are having a "Knee" in your spectrum and care about the exact values of your aperiodic parameters e.g. Knee Frequency

