

Michael Valiadis

Farzin Negahbani

Institute for Neuromodulation and Neurotechnology







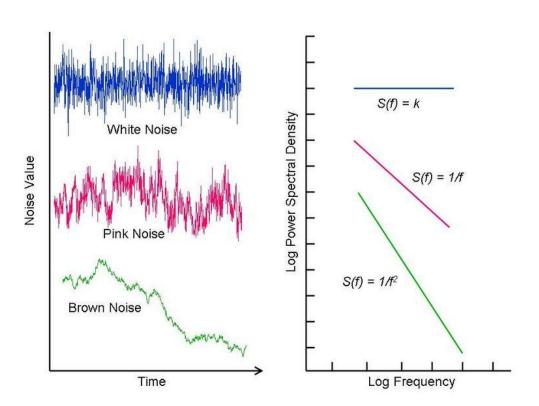
Outline

- Definition & History
- Examples in Neuroscience
- Hypotheses in Neuroscience
- How do we model aperiodic activity
- Tools and frameworks IRASA vs. FOOOF
- Interactive demonstration with GUI
- Limitations and challenges of current methods
- Example with Sleep EEG data
- Tips & Recommendations



Definition & History

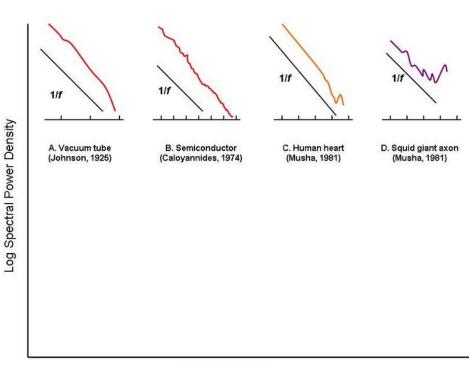
 Power spectral density (PSD) is inversely proportional to frequency, as the frequency increase, the PSD decays linearly in log-log space.





Definition & History

 1/f noise was first observed discovered by Johnson [1] in 1925 in data from an experiment designed to test theory of shot noise in vacuum tubes.

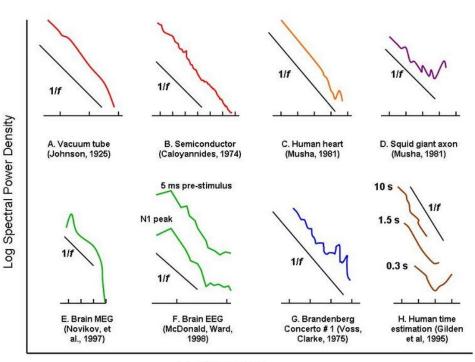


Log Frequency



Definition & History

- 1/f noise was first observed discovered by Johnson [1] in 1925 in data from an experiment designed to test theory of shot noise in vacuum tubes.
- Subsequently observed in semiconductors [2], human heart rhythm [3], squid axons [3], M/EEG [4, 5], musical pieces [6], time perception [7], among others.
- Primacy of neural oscillations [8]



Log Frequency



Examples in Neuroscience

Aperiodic exponent (β) for human voltage spectra: Mean = -3.1 (IQR: -4 to -2.5) for freqs >20 Hz [9]

β	Ref	Year	Recording modality	Frequency	Experimental condition
-0.08	[53]	2019	Scalp EEG (n=5)	20-40 Hz	Anesthesia (Ketamine)
-1.12	[19]	2022	Scalp EEG (n=16, control subjects)	1-40 Hz	Eyes closed
-1.3	[59]	2021	Scalp EEG (n=74, Tourette syndrome)	2-40 Hz	Behavioral experiments
-1.44	[59]	2021	Scalp EEG (n=74, control)	2-40 Hz	Behavioral experiments
-1.48	[19]	2022	Scalp EEG (n=18, stroke patients)	1-40 Hz	Stroke patients
-1.51	[18]	2019	Scalp EEG (n=78, control subjects)	4-50 Hz	Resting state
-1.67	[18]	2019	Scalp EEG (n=76, ADHD subjects)	4-50 Hz	Resting state
-1.84	[10]	2020	Scalp EEG (n=9)	30-45 Hz	Wakefulness
-1.86	[60]	2013	Scalp EEG (n=7, adults)	0.2-30 Hz	Sleep
-1.87	[10]	2020	Scalp EEG (n=14)	30-45 Hz	Resting state
-2.03	[53]	2019	Scalp EEG (n=5)	20-40 Hz	Wakefulness
-2.07	[60]	2013	Scalp EEG (n=15, newborns)	0.2-30 Hz	Sleep
-2.32	[61]	2000	Intracranial EEG (n=5)	0.5-150 Hz	Resting state
-2.33	[12]	2021	Scalp EEG (n=175, T5)	2-48 Hz	NREM sleep
-2.44	[31]	2010	Intracranial EEG (n=5)	1-100 Hz	Wakefulness
-2.48	[53]	2019	Scalp EEG (n=5)	20-40 Hz	Wakefulness
-2.71	[11]	2022	Scalp EEG (n=251)	2-48 Hz	NREM sleep
-2.73	[12]	2021	Scalp EEG (n=175, Fz)	2-48 Hz	NREM sleep
-2.75	[10]	2020	Intracranial EEG (n=12)	30-45 Hz	Wakefulness
-2.87	[31]	2010	Intracranial EEG (n=5)	1-100 Hz	Slow wave sleep
-2.99	[10]	2020	Intracranial EEG (n=10)	30-45 Hz	Wakefulness
-3.1	[10]	2020	Scalp EEG (n=9)	30-45 Hz	Anesthesia
-3.13	[53]	2019	Scalp EEG (n=5)	20-40 Hz	Wakefulness
-3.46	[10]	2020	Scalp EEG (n=14)	30-45 Hz	N3 Sleep
-3.59	[53]	2019	Scalp EEG (n=5)	20-40 Hz	Anesthesia (Xenon)
-3.67	[10]	2020	Scalp EEG (n=14)	30-45 Hz	N2 Sleep
-3.69	[10]	2020	Intracranial EEG (n=10)	30-45 Hz	N3 Sleep
-4	[27]	2009	Intracranial EEG (n=20)	80-500 Hz	Behavioral experiments
-4.15	[10]	2020	Intracranial EEG (n=10)	30-45 Hz	REM sleep
-4.34	[10]	2020	Intracranial EEG (n=12)	30-45 Hz	Anesthesia
-4.36	[53]	2019	Scalp EEG (n=5)	20-40 Hz	Anesthesia (Propofol)
-4.73	[10]	2020	Scalp EEG (n=14)	30-45 Hz	REM sleep



Examples in Neuroscience

Study (year)	Domain Examined	Key Finding	
He (2014), Kello et al. (2010)	Aperiodic component	Introduction and interest in the aperiodic component of 1/f.	
Ouyang et al. (2020), Podvalny et al. (2015), Waschke et al. (2021)	Task	Changes in the 1/f exponent with tasks.	
Bódizs et al. (2021), Dave et al. (2018), Waschke et al. (2017), Cellier et al. (2021), He et al. (2019), Schaworonkow & Voytek (2021), Voytek et al. (2015)	Age	1/f exponent changes with age.	
Muthukumaraswamy & Liley (2018), Stock et al. (2020), Timmermann et al. (2019)	Psychoactive drug administration	1/f changes with drug administration.	
Molina et al. (2020), Robertson et al. (2019), Veerakumar et al. (2019), van Heumen et al. (2021), Ostlund et al. (2021), Karalunas et al. (2022)	Disease	1/f exponent correlation with diseases.	
Halgren et al. (2021)	Cortical Depth	1/f decreases with cortical depth.	
Gao et al. (2017)	Computational modeling	1/f exponent β as estimator of excitation—inhibition balance.	
Lendner et al. (2020), Miskovic et al. (2019), Colombo et al. (2019), Muthukumaraswamy & Liley (2018), Waschke et al. (2021), Zhou et al. (2021)	Consciousness States	Differences in 1/f exponent in NREM sleep, anesthesia vs. awake states.	

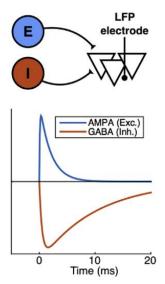
*Derived from [8]

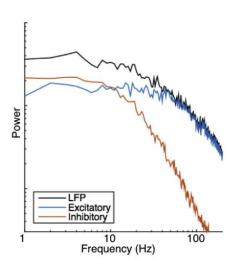


Hypotheses in Neuroscience

What could it mean?

- Neurophysiological interpretation
 - Several computational models indicate that desynchronized non-oscillatory brain activity correlates with population excitation-to-inhibition balance (E-I Ratio) [10-11]



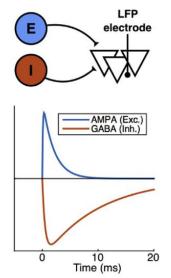


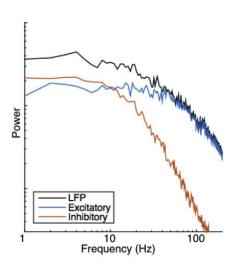


Hypotheses in Neuroscience

What could it mean?

- Neurophysiological interpretation
 - Several computational models indicate that desynchronized non-oscillatory brain activity correlates with population excitation-to-inhibition balance (E-I Ratio) [10-11]
 - Offset reflects neuronal population spiking, whereas exponent relates to the integration of synaptic currents [14]



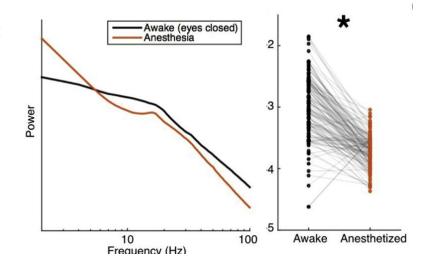




Hypotheses in Neuroscience

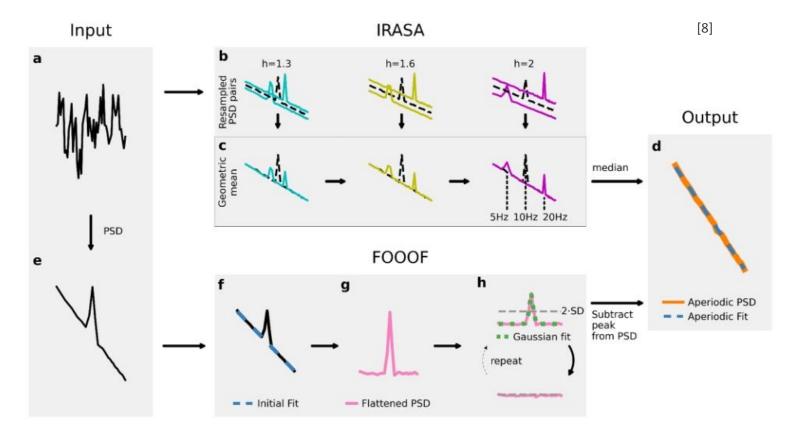
What could it mean?

- Neurophysiological interpretation
 - Several computational models indicate that desynchronized non-oscillatory brain activity correlates with population excitation-to-inhibition balance (E-I Ratio) [10-11]
 - Conscious states (increased excitation) vs unconscious states (increased inhibition)
 [8]
 - (i.e., larger 1/f exponents observed for NREM sleep and anesthesia compared to wakefulness)





How to model aperiodic activity

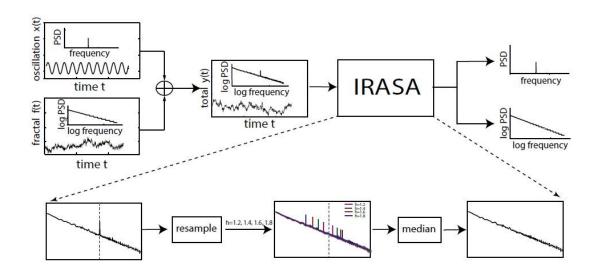




Tools and frameworks - IRASA

Step 1: Compute the original power spectral density (PSD).

Step 2: Resample the EEG data by multiple non-integer factors and their reciprocals (h and 1/h)



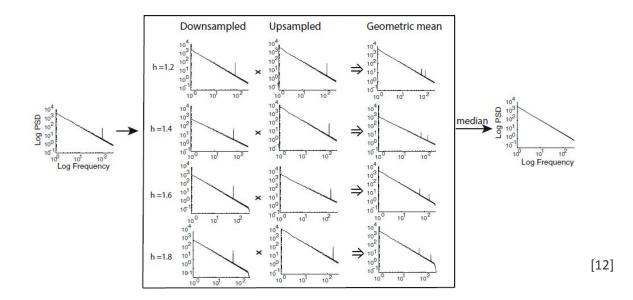


[12]

Tools and frameworks - IRASA

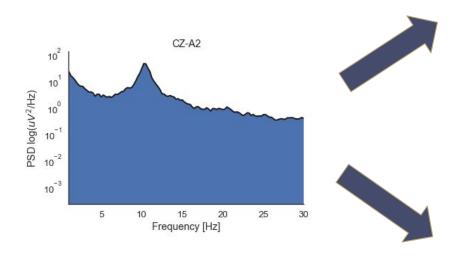
Step 3: For each resampled signal pair, compute the PSD and then determine their geometric mean; this process shifts oscillatory component power by a varying frequency offset while keeping the fractal component's power consistent.

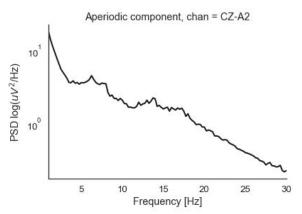
Step 4: Extract the fractal component's power spectrum by finding the median PSD of the resampled signals, and subtract this from the original to estimate the oscillatory component's power spectrum.

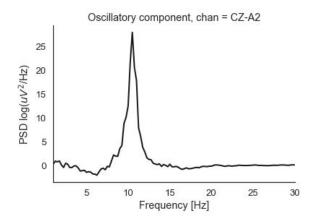




Tools and frameworks - IRASA









Tools and frameworks - FOOOF

Multi-Gaussian fit using Fit and remove [13] Gaussians iteration parameters - Peak Fitted Threshold Fit aperiodic signal peaks Gaussian fit log(power) Remove Gaussians Iterate from original PSD 10 20 30 Frequency (Hz) Gaussian fit Remove aperiodic signal Threshold Halt fitting at Re-fit aperiodic noise floor



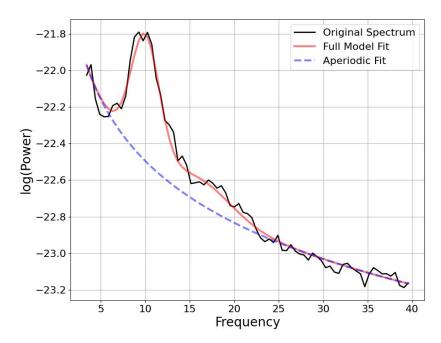
Combine

h Assess goodness of fit

Final fit

Tools and frameworks - FOOOF

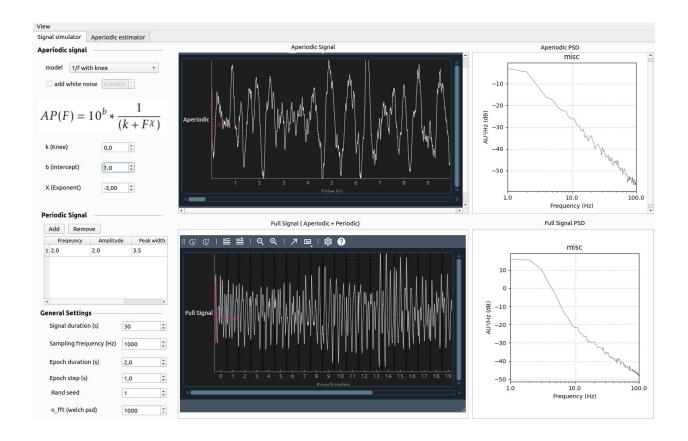
Resulting goodness of fit metrics (i.e., fit error & R^2)



Full model fit of the power spectrum



Interactive demonstration with GUI





Interactive demonstration with GUI

- All workshop materials are available at:
 - https://github.com/Farzin-Negahbani/NeNa aperiodic GUI
 - https://github.com/mvaliadis/2023 NENA Aperiodic Workshop
- To setup the repository:
 - a. git clone git@github.com:Farzin-Negahbani/NeNa_aperiodic_GUI.git
 - b. cd gui
 - c. conda create -n aperiodic python=3.9.7
 - d. conda activate aperiodic
 - e. pip install -r requirements.txt
- To run the GUI:
 - a. python gui.py



Demonstrations

- 1. Pick higher freq band for fitting when having low frequency oscillations.
 - a. E.g. CF= 2 hz, amp= 2, width=3, use 1-30 hz and 30-60 hz for fitting

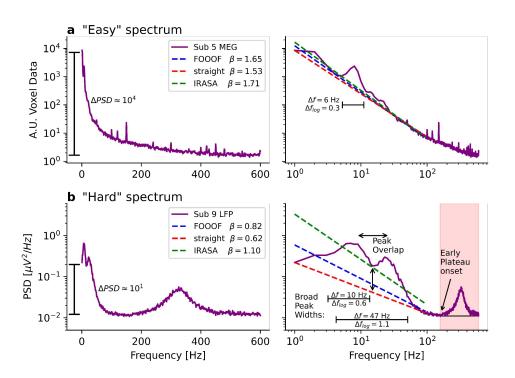
2. Add gaussian noise and increase the noise level and observe the spectral plateau. Try changing fitting range to exclude the plateau.

3. Change h_max parameter and observe change in fit of IRASA.



Limitations and challenges of current methods

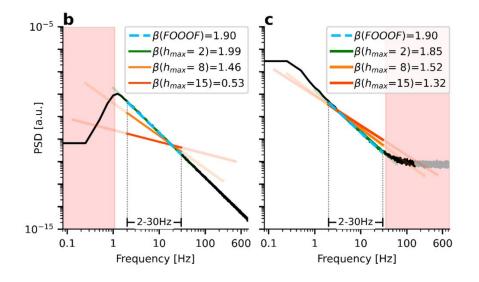
- Main challenges of FOOOF [8]:
 - 1/f disruption from spectral plateaus
 - Avoiding oscillations that cross fitting range boundaries
 - Not sensitive to oscillatory peaks that are not clearly distinguishable





Limitations and challenges of current methods

- Main challenges of IRASA [8]:
 - Evaluated frequency range is larger than the fitting range
 - Broad peak widths require large resampling factors
 - Not sensitive to oscillatory peaks that are not clearly distinguishable
 - Computational speed





• Cleveland Family Study (Sleep EEG) Data (n = 50)

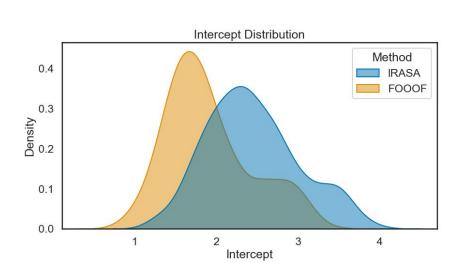




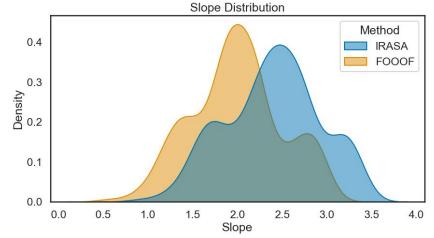
- Cleveland Family Study (Sleep EEG) Data (n = 50)
- Correlation between IRASA and FOOOF:

o Intercept: 0.9707

Slope: 0.9893

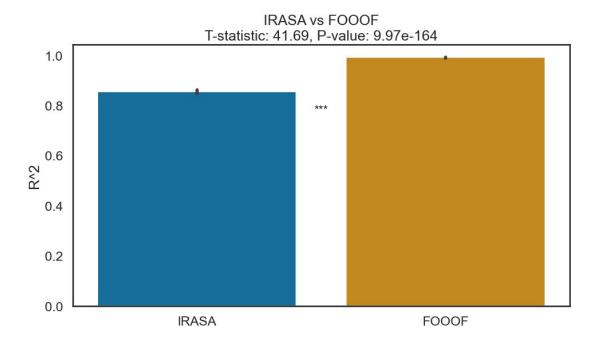






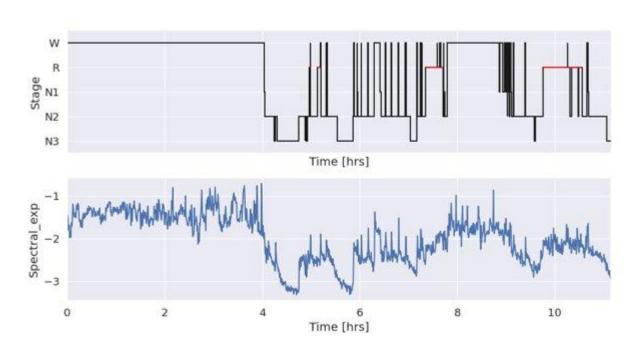


Goodness of fit comparison



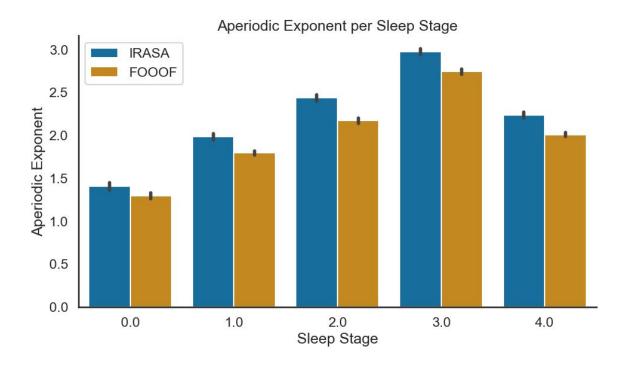


Sleep Stage Differences (Example Subject with IRASA)



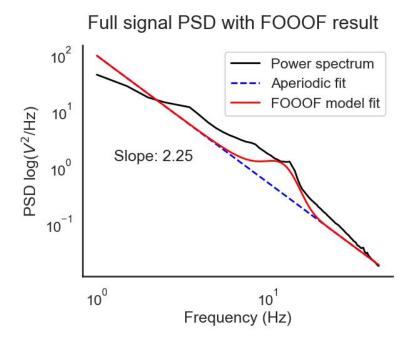


Sleep Stage Differences (Group level):

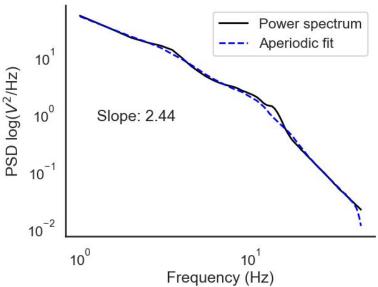




Sleep Stage Comparison (NREM2)



Full signal PSD with IRASA result





Tips & Recommendations

- Spend time looking at your raw PSDs!
 - If there's too many overlapping peaks, avoid fitting aperiodic component
 - Decide on maximal of number of peaks -> go low
 - You may need to model the knee!
- Use a fitting range at higher frequencies (e.g., 40–60 Hz) to avoid distortion from low-frequency oscillation



Tips & Recommendations

- Spend time looking at your raw PSDs!
 - If there's too many overlapping peaks, avoid fitting aperiodic component
 - Decide on maximal of number of peaks -> go low
 - You may need to model the knee!
- Use a fitting range at higher frequencies (e.g., 40–60 Hz) to avoid distortion from low-frequency oscillation
- Choose h_{max} as small as possible but large enough to obtain peak-free estimates of the aperiodic component

$$f_{\text{eval. min}} = f_{\text{fit min}}/h_{\text{max}}$$

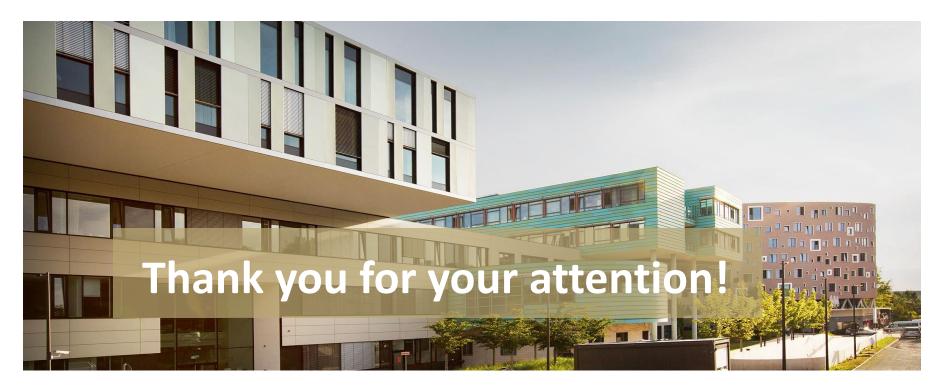
$$f_{\text{eval. max}} = f_{\text{fit max}} \cdot h_{\text{max}}$$



References

- 1. Johnson, J. B. (1925). The Schottky effect in low frequency circuits. *Physical review*, 26(1), 71.
- 2. Caloyannides, M. A. (1974). Microcycle spectral estimates of 1/f noise in semiconductors. *Journal of Applied Physics*, 45(1), 307-316.
- 3. Musha, T., & Yamamoto, M. (1997, October). 1/f fluctuations in biological systems. In *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society.'Magnificent Milestones and Emerging Opportunities in Medical Engineering'(Cat. No. 97CH36136)* (Vol. 6, pp. 2692-2697). IEEE.
- 4. Novikov, E., Novikov, A., Shannahoff-Khalsa, D., Schwartz, B., & Wright, J. (1997). Scale-similar activity in the brain. *Physical Review E*, 56(3), R2387.
- 5. Ward, L. M. (2002). *Dynamical cognitive science*. MIT press.
- 6. Voss, R. F., & Clarke, J. (1975). 1/f noise in speech and music. *Nature*, 258(5533), 317-318.
- 7. Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/f noise in human cognition. *Science*, 267(5205), 1837-1839.
- 8. Gerster, M., Waterstraat, G., Litvak, V., Lehnertz, K., Schnitzler, A., Florin, E., ... & Nikulin, V. (2022). Separating neural oscillations from aperiodic 1/f activity: challenges and recommendations. *Neuroinformatics*, 20(4), 991-1012.
- 9. Kramer, M. A., & Chu, C. J. (2023). The 1/f-like behavior of neural field spectra are a natural consequence of noise driven brain dynamics. *bioRxiv*, 2023-03.
- 10. Gao, R., Peterson, E. J., & Voytek, B. (2017). Inferring synaptic excitation/inhibition balance from field potentials. *Neuroimage*, 158, 70-78.
- 11. Chini, M., Pfeffer, T., & Hanganu-Opatz, I. (2022). An increase of inhibition drives the developmental decorrelation of neural activity. *Elife*, *11*, e78811.
- 12. Wen, H., & Liu, Z. (2016). Separating fractal and oscillatory components in the power spectrum of neurophysiological signal. *Brain topography*, *29*, 13-26.
- Donoghue, T., Haller, M., Peterson, E. J., Varma, P., Sebastian, P., Gao, R., ... & Voytek, B. (2020). Parameterizing neural power spectra into periodic and aperiodic components. *Nature neuroscience*, *23*(12), 1655-1665.
- 14. Voytek, B., & Knight, R. T. (2015). Dynamic network communication as a unifying neural basis for cognition, development, aging, and disease. *Biological psychiatry*, 77(12), 1089-1097.







Tübingen





