Propofol anesthesia destabilizes neural dynamics across cortex

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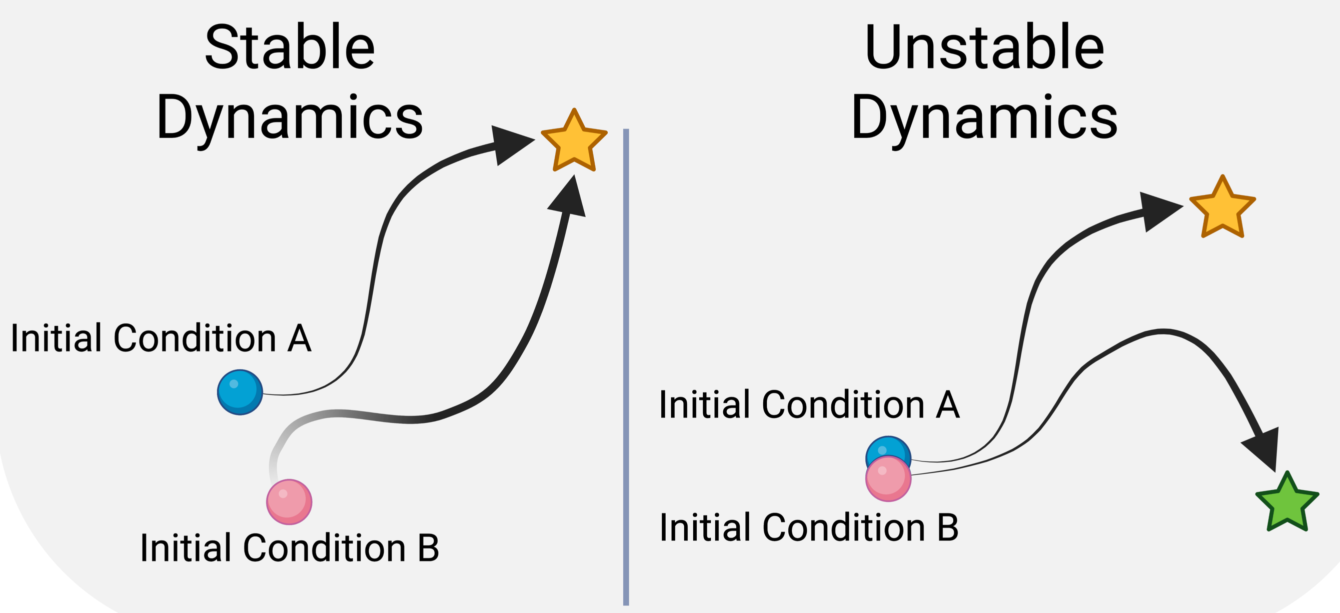
SCAN ME

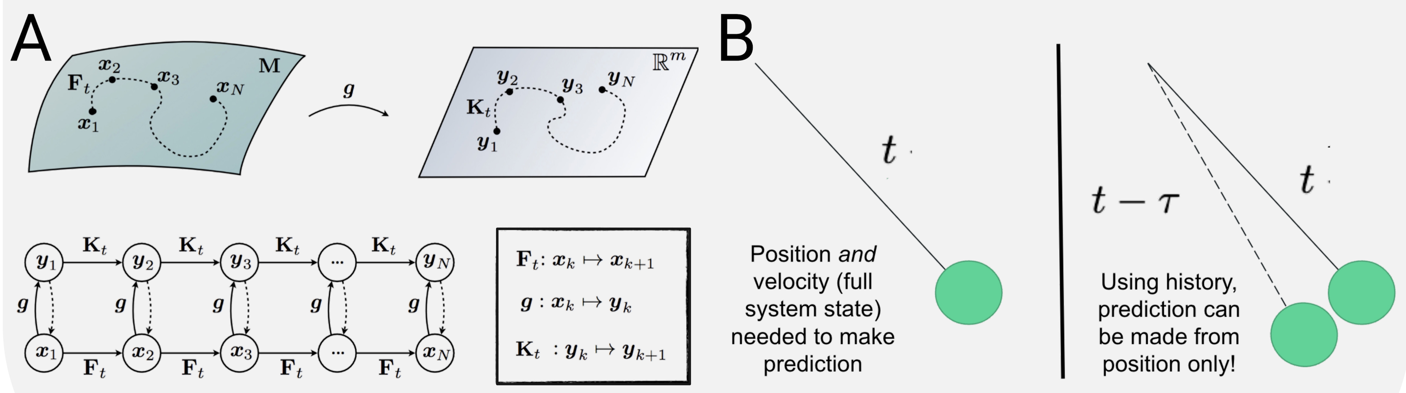
INTRODUCTION

- **The neural basis of consciousness is unknown** – anesthesia allows exploration of the transition between consciousness and unconsciousness.
- Theories suggest that dynamic stability is critical to cortical function[1-4]. Networks balance flexibility with reliability. Network activity needs to stay "on track", be dynamic yet constrained enough to perform consistent computations.
- **Anesthesia could stabilize or destabilize neural dynamics.** Current approaches have not resolved this[5,6].
- We leveraged tools from dynamical systems theory.



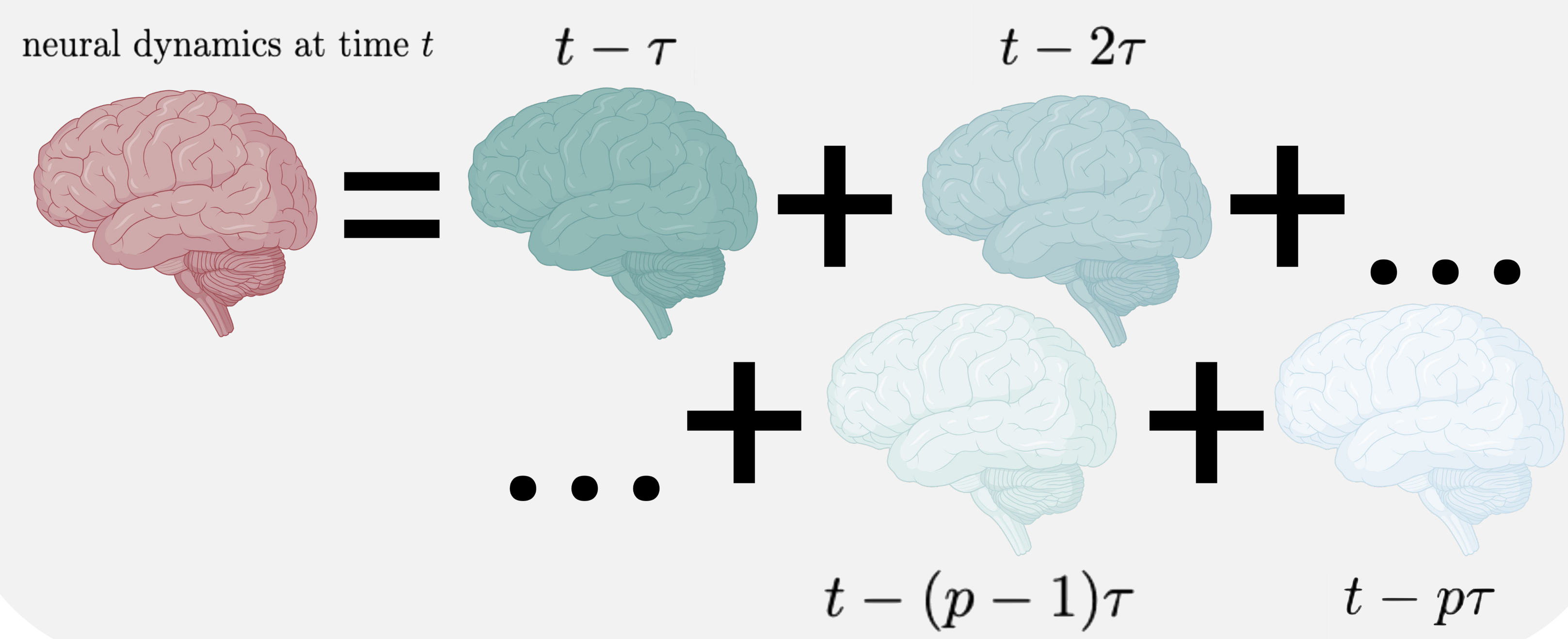
METHODS
Model Building

By looking backwards in time, we can find a fully linear representation of the brain's complex nonlinear dynamics. **We can reduce complex dynamics to a simple relationship (coefficients) between states across time[7-13].**



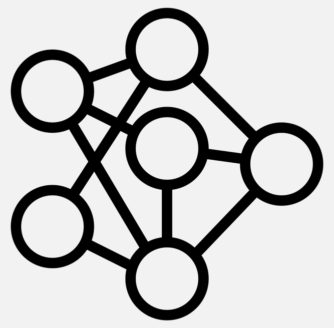
METHODS
Stability Estimation

Using methods from linear delay differential equations (DDEs), we estimate stability by **discounting the impact of previous states on dynamics[14, 15].**

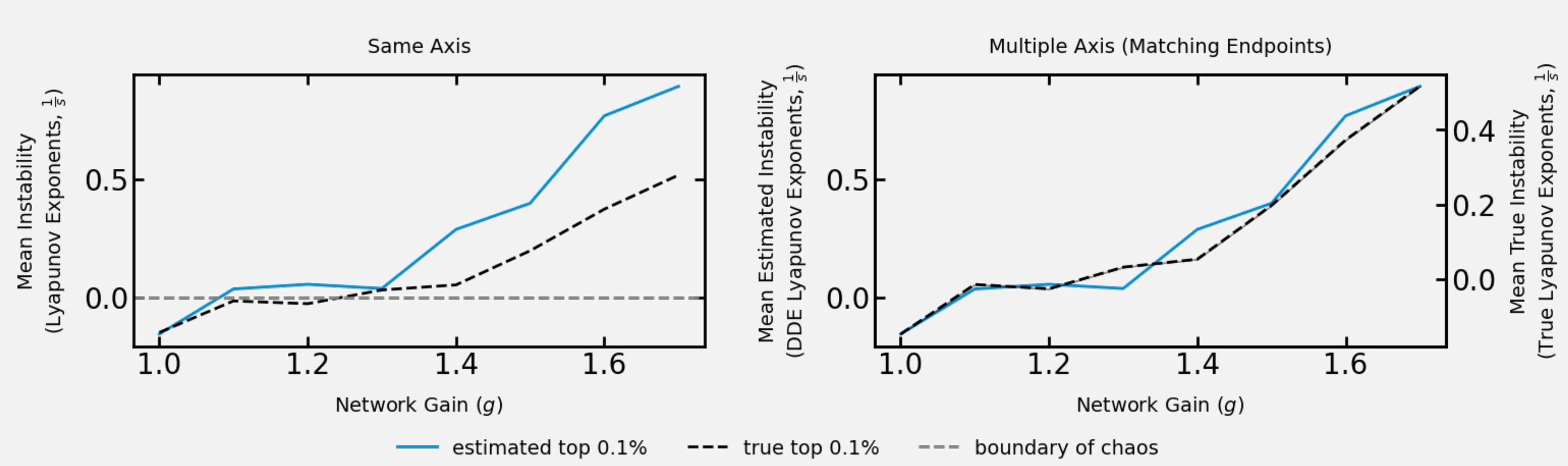


RESULTS
Accurately stability estimation in simulation

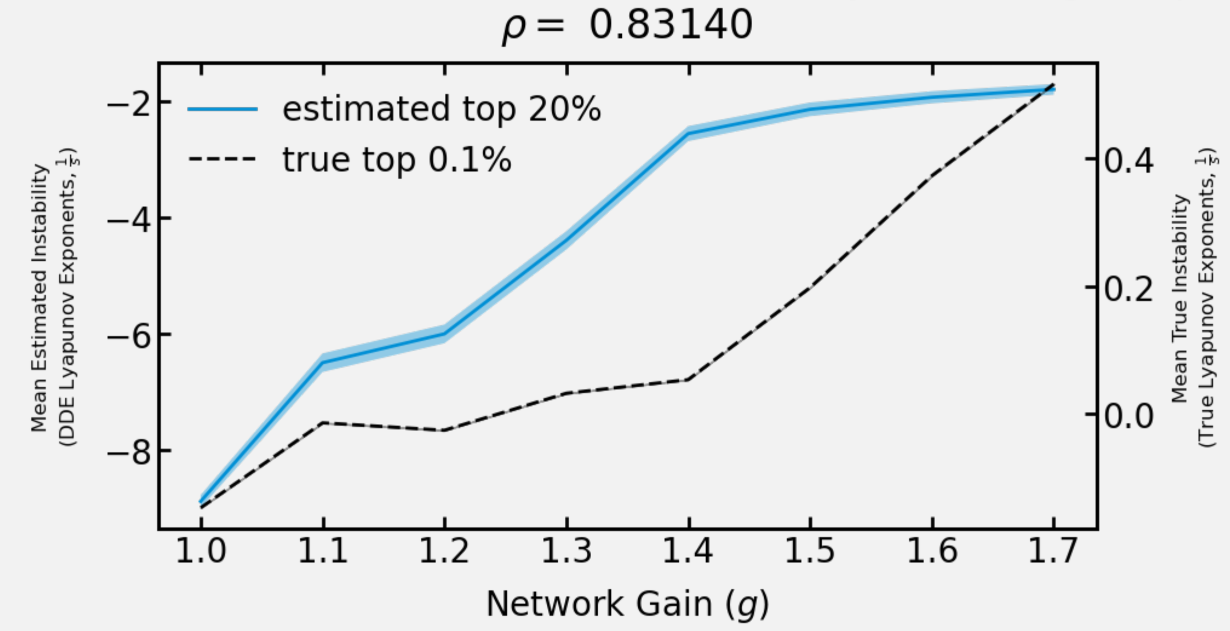
We predicted relative changes in stability between RNNs using only partial observation (50 of 512 neurons observed)



Chaotic Network Estimated vs. True Instability ($\rho = 0.98426$)

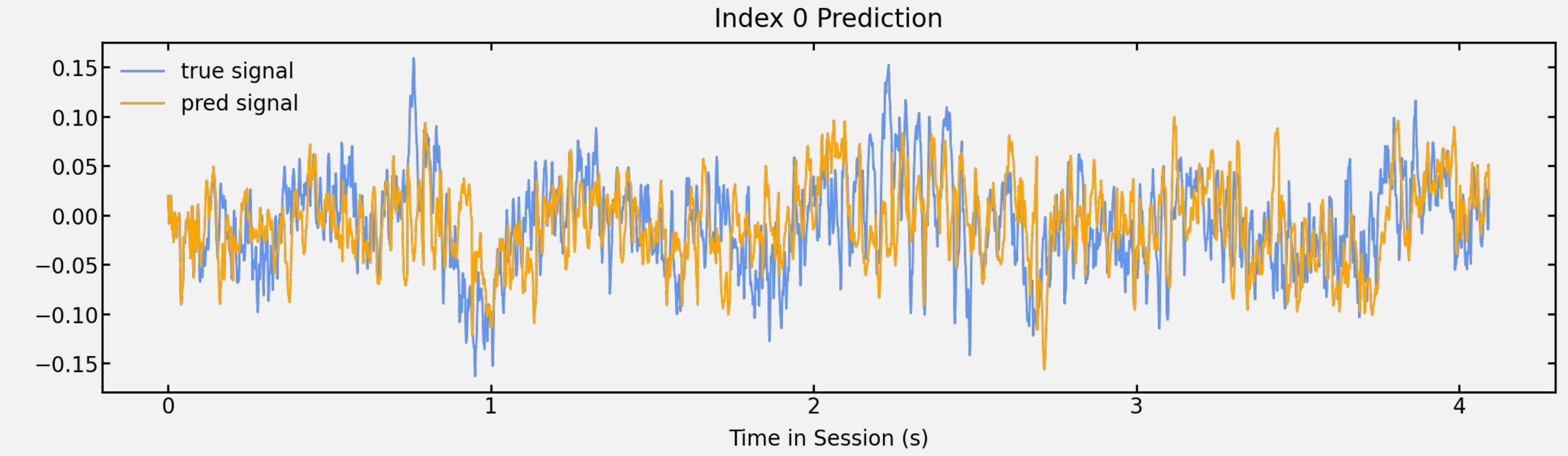


Chaotic Network Estimated vs. True Instability (Matching Endpoints)
$\rho = 0.83140$



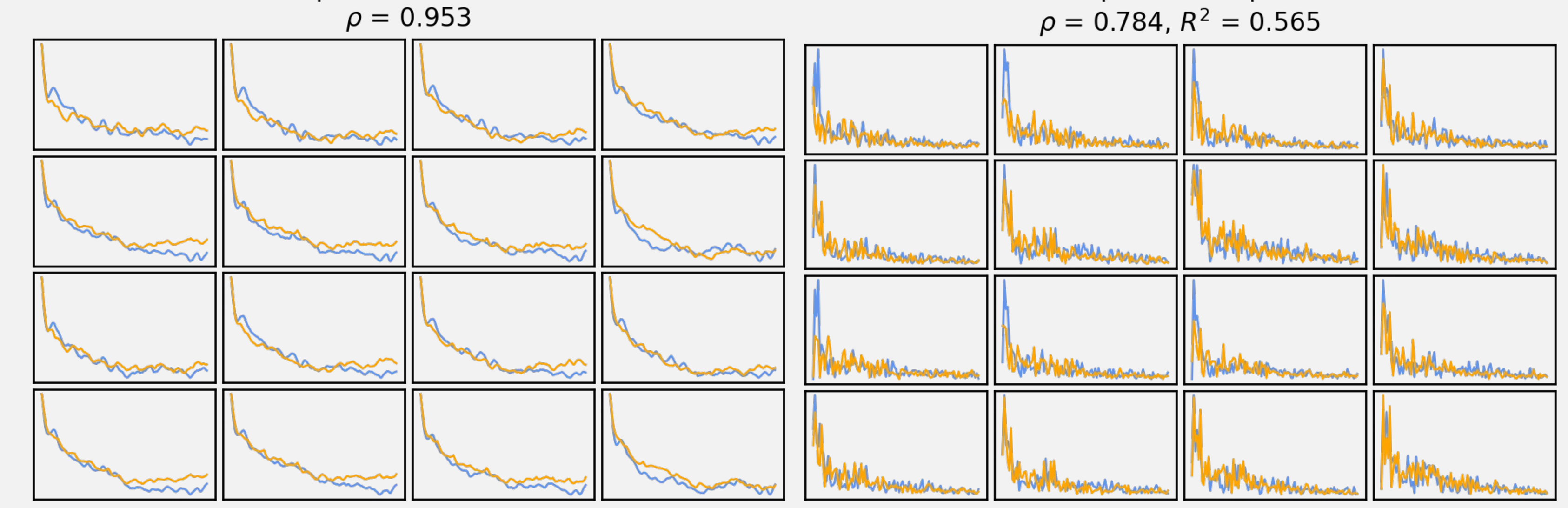
RESULTS
Propofol destabilizes neural activity

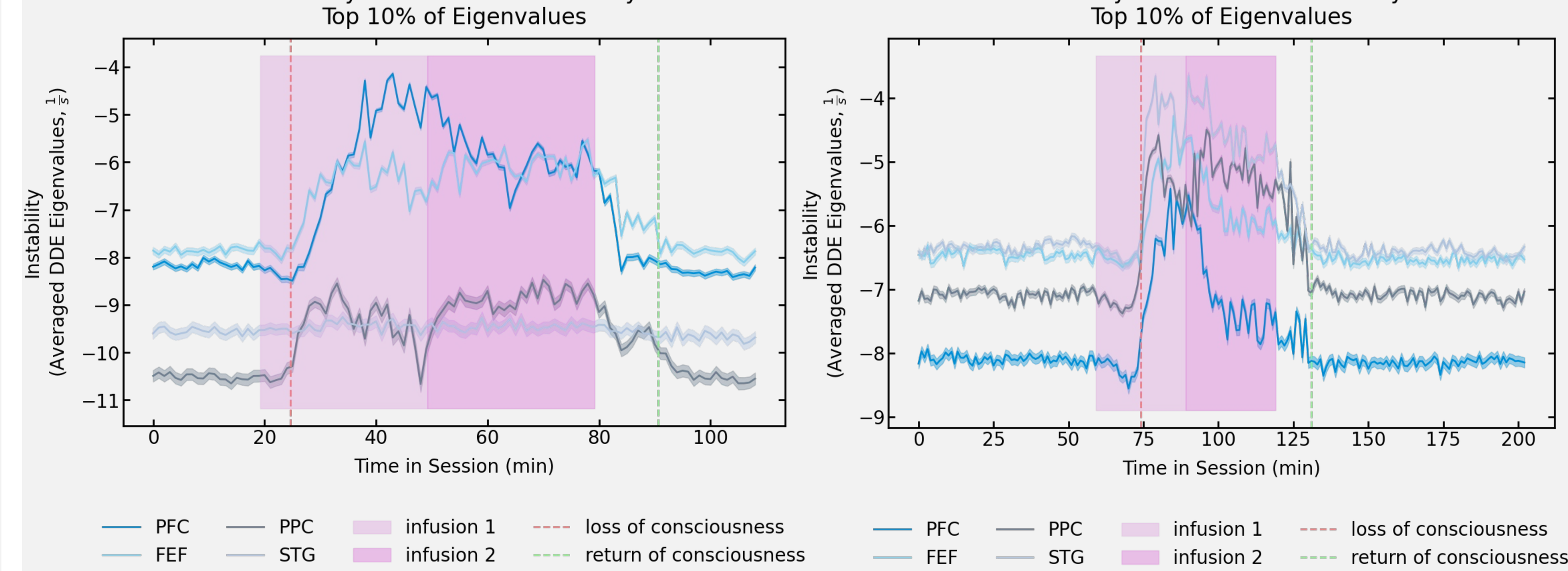
Model Performance on Test Signal
Wakeful Data (p = 93, reseed = 50 ms)
Index 0 Prediction



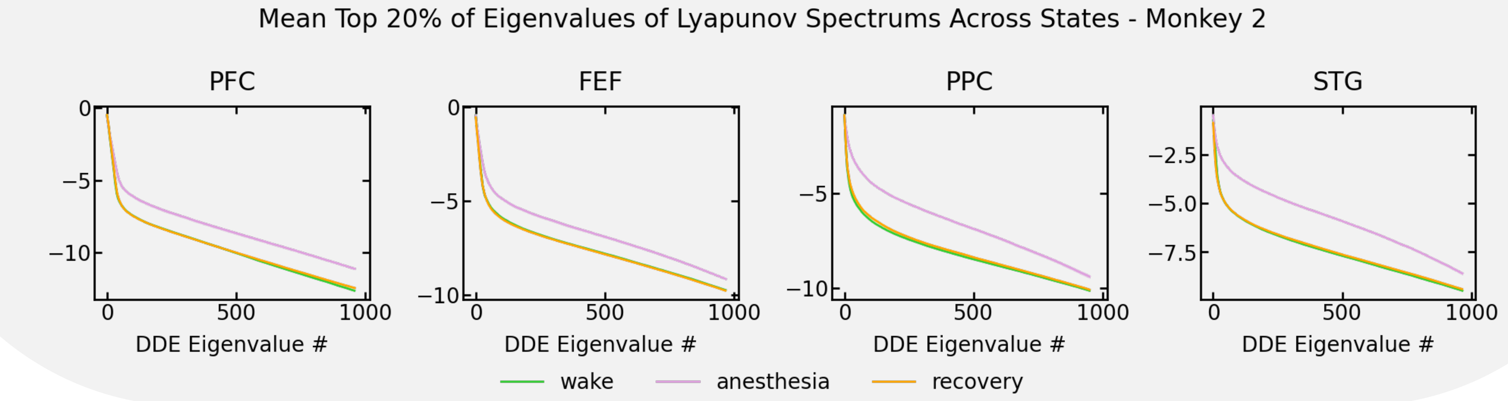
Example Autocorrelations
$\rho = 0.953$

Example Power Spectra
$\rho = 0.784$, $R^2 = 0.565$





Mean Top 20% of Eigenvalues of Lyapunov Spectrums Across States - Monkey 2



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