OKINAWA INSTITUTE OF SCIENCE AND TECHNOLOGY GRADUATE UNIVERSITY
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Maximizing Transfer Entropy in Agent Based Models

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Introduction

- The entropic brain hypothesis (Carhart-Harris et al., 2014) proposes that entropy can be viewed as an index of the state of consciousness that spans the spectrum of cognitive states between high entropy associated with flexible cognition and low entropy correlated with inflexible cognition.

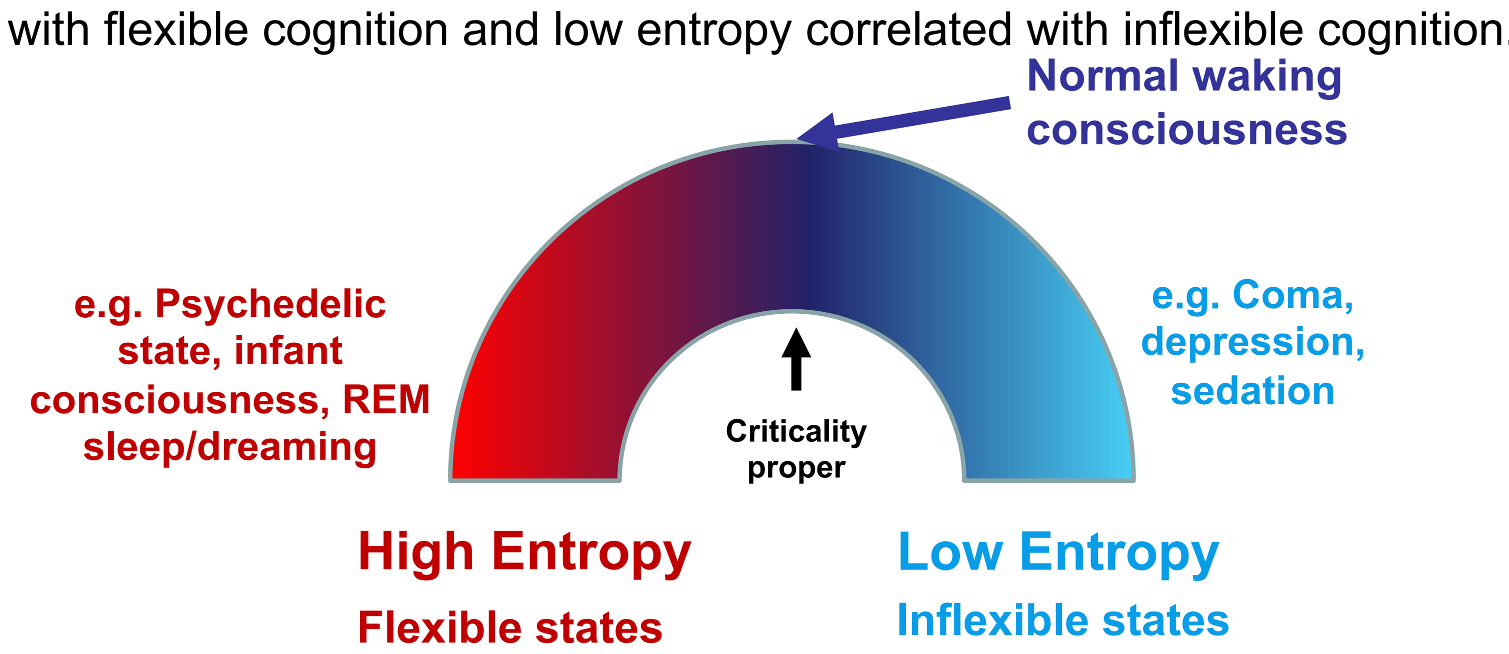


Figure adapted from Carhart-Harris et al. (2014).

- This raises the question of which entropy-based measure of neural complexity is maximized at the most adaptive levels of consciousness in the middle of the spectrum. While simple Shannon entropy seems like an easy choice, it is likely to be maximal when the system's behavior is close to random. It has been argued that a more proper measure is one that reflects a balance between integration and segregation of the system's components. This measure is often defined in terms of transfer entropy (Mäki-Marttunen et al., 2013; Tononi, Sporns & Edelman, 1994).
- In this work we compare Shannon entropy (SE) and transfer entropy (TE) in terms of:
  - their general characteristics derived from applying these measures to various cases of simulated artificial data
  - their downstream effects on behavior when artificial agents are evolved to maximize neural complexity indexed by these two measures

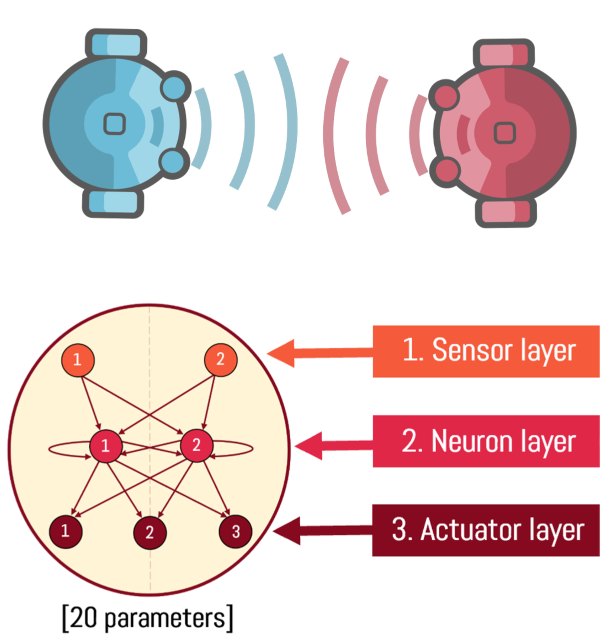
Methods

- **Simulated two-dimensional data**

100 samples of artificial 2D data of size N=2000 were generated for each of the following cases:

- uncorrelated random arrays from normal and uniform distributions
- constant arrays of a single value ([1.0, 1.0,…], [1.0, 1.0, …])
- correlated arrays of constant values ([1.0, 1.0,…], [2.0, 2.0, …])
- uniform filling of all 100x100 bins (here N=10,000), in regular and random order
- 1 random array and 2nd array correlated with the 1st at various levels of delayed correlation
- positions of a coupled spring mass system with various masses, spring lengths and constants

- **Interactive agents based on Candadai et al. (2019) model**

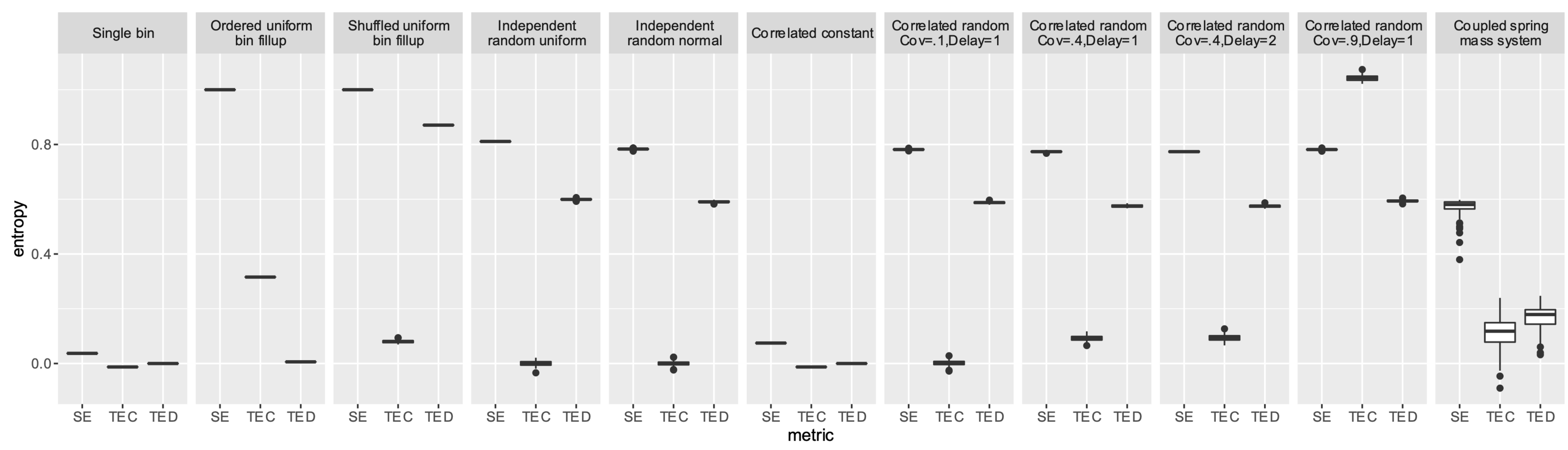


- Pairs of embodied agents in a simulated 2-dimensional environment. Each agent has two acoustic sensors, one acoustic emitter and two motors driving wheels.
- Neural architecture of an agent: Consisting in 3 layers (sensor, neuron and actuator layers) . The neuron layer has two neurons.
- Evolutionary algorithm: Optimization of the parameters of the neural controllers to maximize each agent's neural entropy (Shannon Entropy or TE).

Results

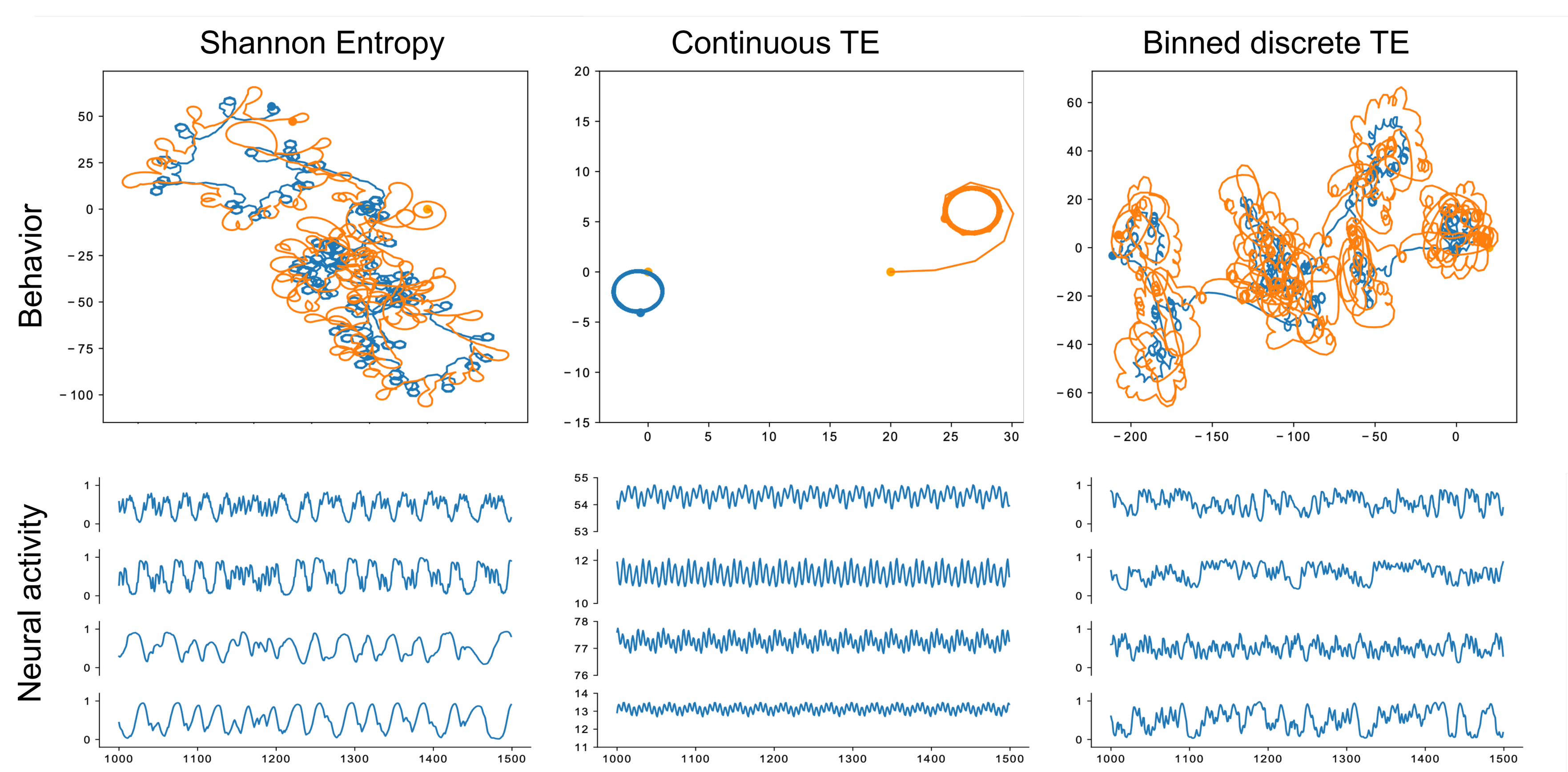
Comparison between Shannon Entropy and Transfer Entropy

- **Using artificial two-dimensional data**



Plots of mean entropy values for Shannon entropy (SE), transfer entropy obtained separately for original continuous values using KSG estimator (TEC) and values discretized into 100 bins using discrete estimator (TED).

- **Using agent-based modeling of two agents in interactive scenario**



Top row: plots of 2 agent movement trajectories. Bottom row: plots of the neural output of both agent's 2 neurons (top-most N1 of agent 1, then N2 of agent 1, N1 of agent 2, N2 of agent 2).

Conclusions

1. **On artificial data**
   - TEC and TED do not behave in completely parallel manner
   - TEC is predictably higher for ordered compared to shuffled uniform data while TED is surprisingly high for shuffled uniform data
   - for data in which one time series is random while the other highly correlated, TEC is more sensitive to higher correlation than TED
   - dependencies in oscillatory data are characterized as entropic by SE
   - SE is maximized for random data, especially when drawn from a uniform distribution
   - SE is not sensitive to the order of data points
2. **On data produced by agent-based modeling**
   - TEC leads to oscillatory behavior in neural activity. However, its range is extremely restricted and does not translate into behavioral complexity. This in turn, does not allow the agents to engage in interesting interactive patterns which could lead to their reciprocal coupling and increase their neural complexity (see Candadai et al., 2019).
   - TED produces neural and behavioral complexity, which seems even higher than that produced by maximizing SE. Whether this can lead to overall more adaptive behaviors needs to be further investigated.

References

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