Random Reservoirs Rule! (at Remembering)

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Introduction

Reservoir computing is a framework where a fixed recurrent neural network (RNN) is used to process input signals and perform computations. Reservoirs are typically randomly initialised, but it is not fully known how connectivity affects performance, and whether particular structures might yield advantages on specific or generic tasks. Simpler topologies often perform equally well as more complex networks on prediction tasks [1]. We check performance differences of reservoirs on four task types using the connectomes of C. elegans and drosophila larval mushroom body [2], [3] in comparison with varying degrees of randomisation.

Background: Reservoir Computing

In reservoir computing a random RNN is used as a fixed, large-scale dynamical system, called the reservoir, to process temporal signals and perform computations [4]. Reservoirs have rich dynamics allowing complex non-linear transformations of their input. The dynamics are driven by the equation

$$\boldsymbol{x}(t+1) = (1-\alpha)\boldsymbol{x}(t) + \alpha f(\boldsymbol{W}\boldsymbol{x}(t) + \boldsymbol{W}_{\text{in}}\boldsymbol{u}_{\text{in}}(t))$$

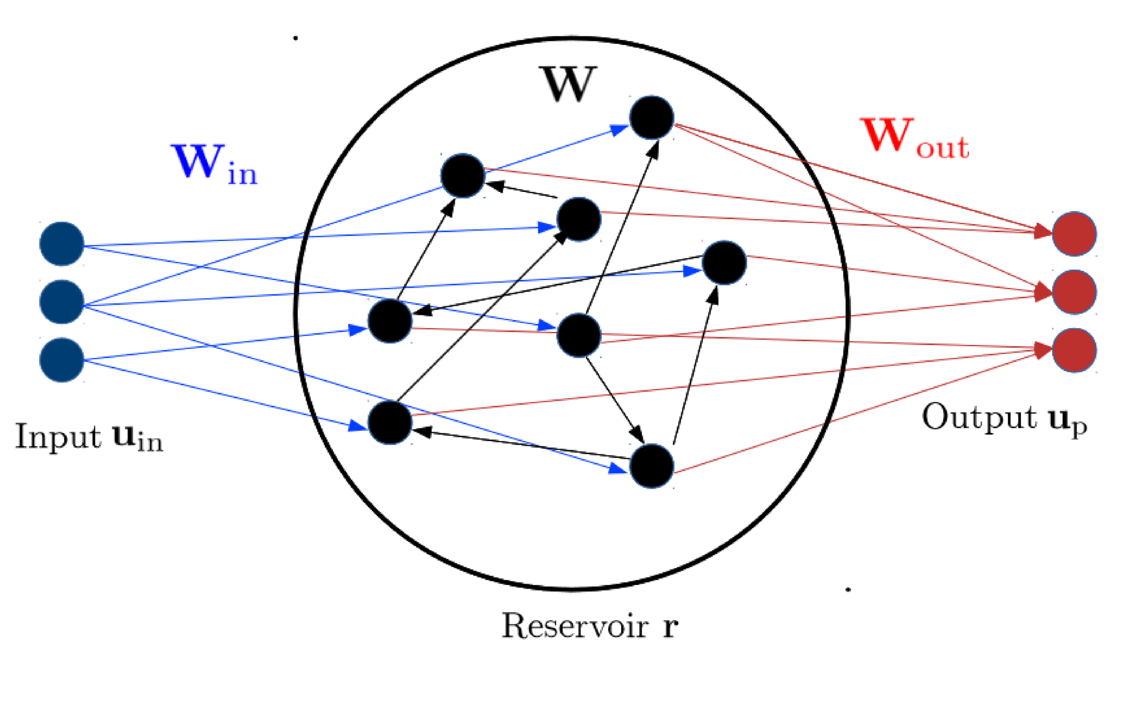

Figure 1. Adapted [5] illustration of the setup of a reservoir.

Brain Connectomes

In this work we used the synaptic resolution connectomes of drosophila larval mushroom body and male C. elegans [2], [3]. These networks have similar sizes ($N \approx 380$).

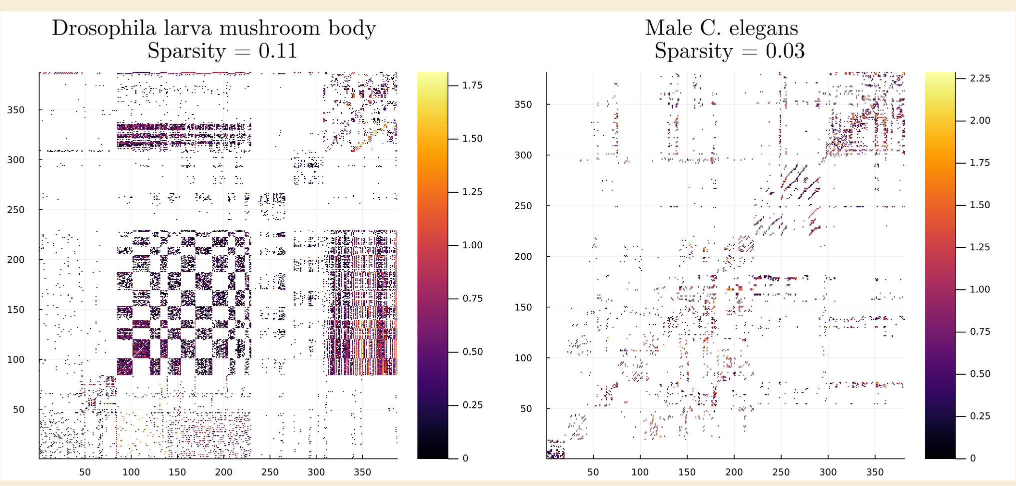

Figure 2. Heatmap plots (log scale) of the connectivity matrices.

Different Computational Tasks

<u>Working memory task:</u> Random inputs $X(t) \sim \text{Uniform}(-0.5, 0.5)$ are presented to the network, and it learns delayed versions. Each output neuron Y_τ presents the input delayed by τ. Performance is calculated as the cumulative squared Pearson correlation coefficient:

$$\text{Working Memory Capacity} = \sum_\tau \rho^2(y_i, \hat{y}_i)$$

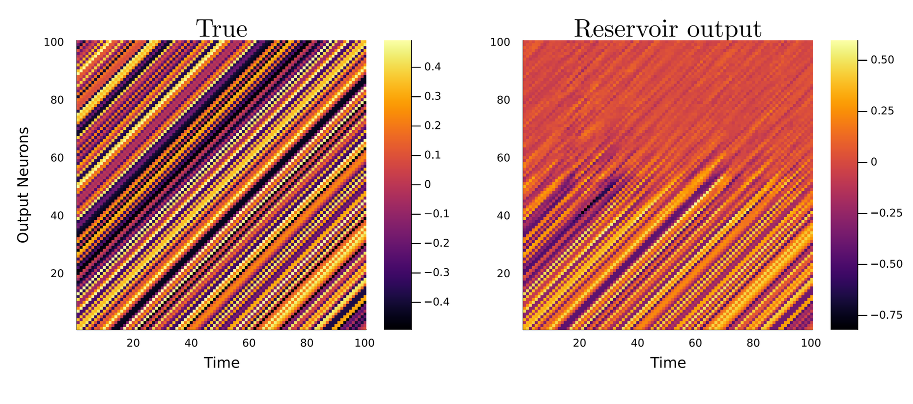

Figure 3. Working Memory Task: True data (left) and example output (right)

<u>Sequence recall:</u> A random sequence is presented to the reservoir and following a cue the reservoir must reproduce it. It is trained over 200 trials and tested for 50. The squared Pearson correlation coefficient between the true output and the reservoir output is computed.

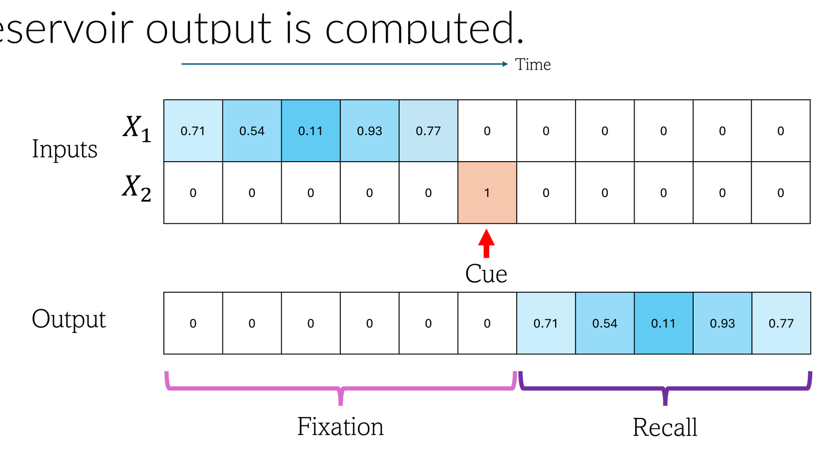

Figure 4. Sequence Recall Task

<u>Perceptual decision making task:</u> A noisy visual stimulus in the form of random dot motion (where dots move with a specified coherence level) is presented to the reservoir. The output provides a decision of the coherence level. Reciprocal mean squared error is used as a measure of performance:

$$\text{Decision Making Performance} = \left(\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2\right)^{-1}$$

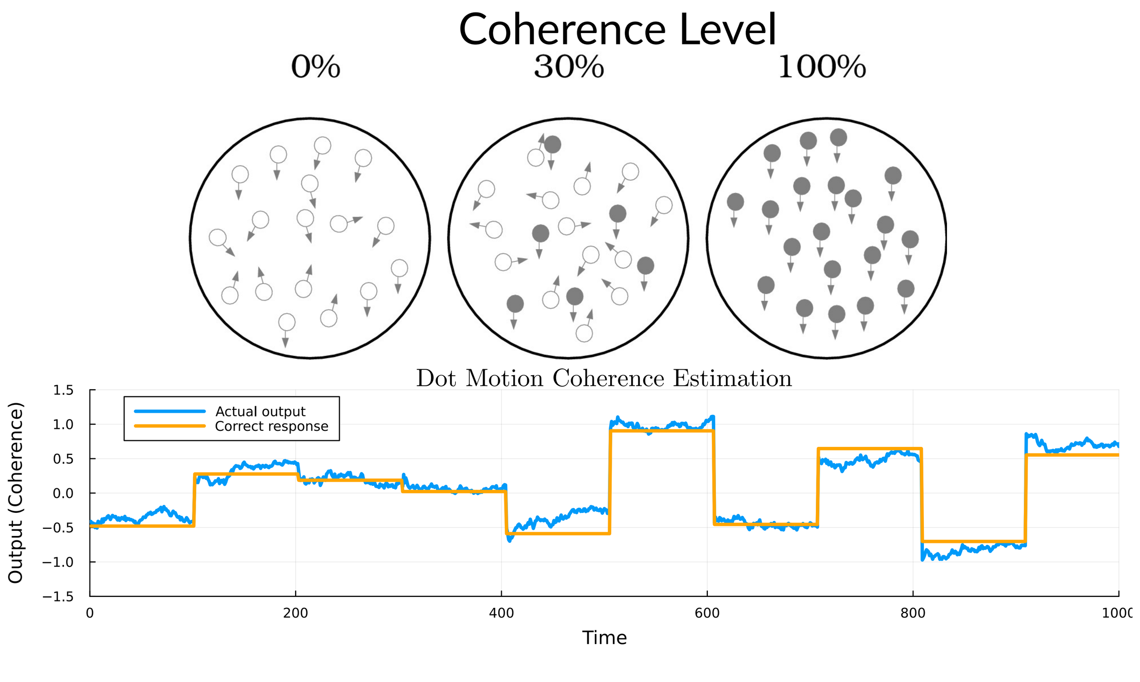

Figure 5. Perceptual Decision Making Task

<u>Chaotic time-series prediction:</u> We train the reservoir on a set of Lorenz data [4], [6], and then provide the system with a random point on the Lorenz trajectory, and measure the valid Lyapunov time for which the reservoir can accurately predict the true trajectory. We calculate the normalised mean squared error,

$$\text{NMSE} = \frac{\|\boldsymbol{u}(t) - \tilde{\boldsymbol{u}}(t)\|}{\sqrt{\langle\|\boldsymbol{u}(t)\|^2\rangle}}$$

and we measure, in Lyapunov time, the point at which the predicted trajectory exceeds a specified NMSE threshold, set at 0.5.

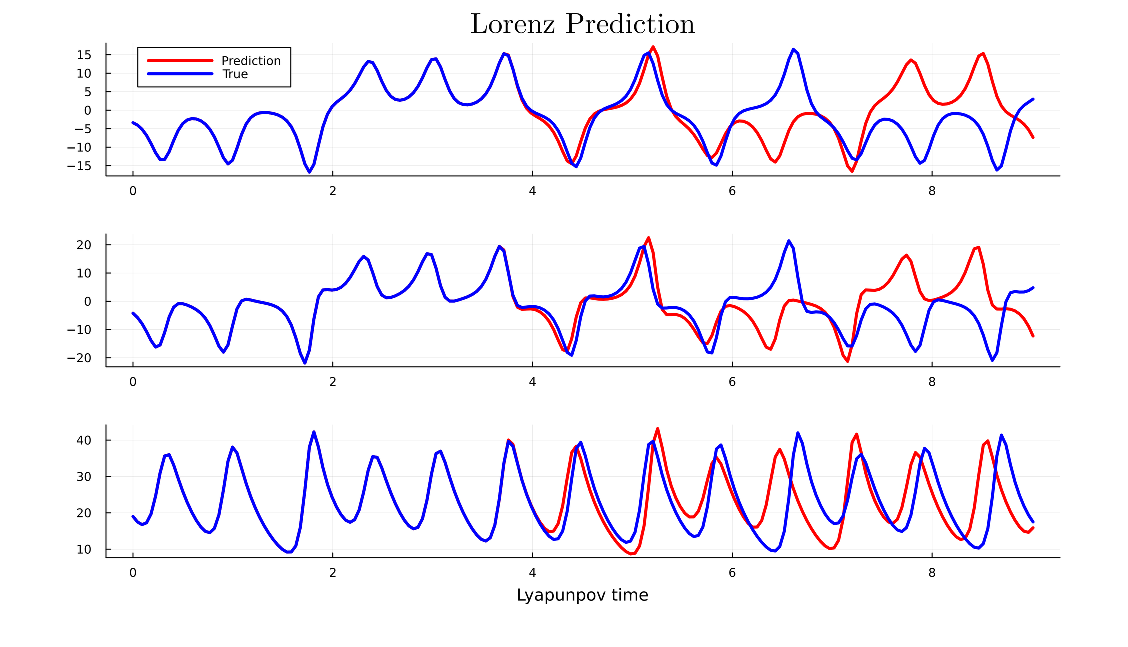

Figure 6. Lorenz Prediction Task

Randomisation Methods

We compare the performances of connectome-based reservoirs and *equivalent random reservoirs*, ensuring the same size, sparsity, and spectral radius.

1. <u>Degrees of randomisation:</u> $0, 0.25, 0.5, 0.75$, and 1.0 (where 0 is the original connectome, and 1.0 is full randomisation of connectome weights). We include "Totally Random" reservoirs with a uniform distribution of weights.
2. We then randomise the connectomes while <u>preserving the topology</u>, i.e. uniformly randomise the nonzero weights while maintaining the zero weights.
3. <u>Varying the excitation to inhibition ratio</u> within the reservoir network (ratio of positive to negative weights in $\boldsymbol{W}$). The ratios we implement in the reservoirs are $1:0$ (entirely excitatory), $4:1$ (weighted towards excitation), and $1:1$ (equal excitation and inhibition). These are allocated randomly.

1. Results: Randomisation Levels

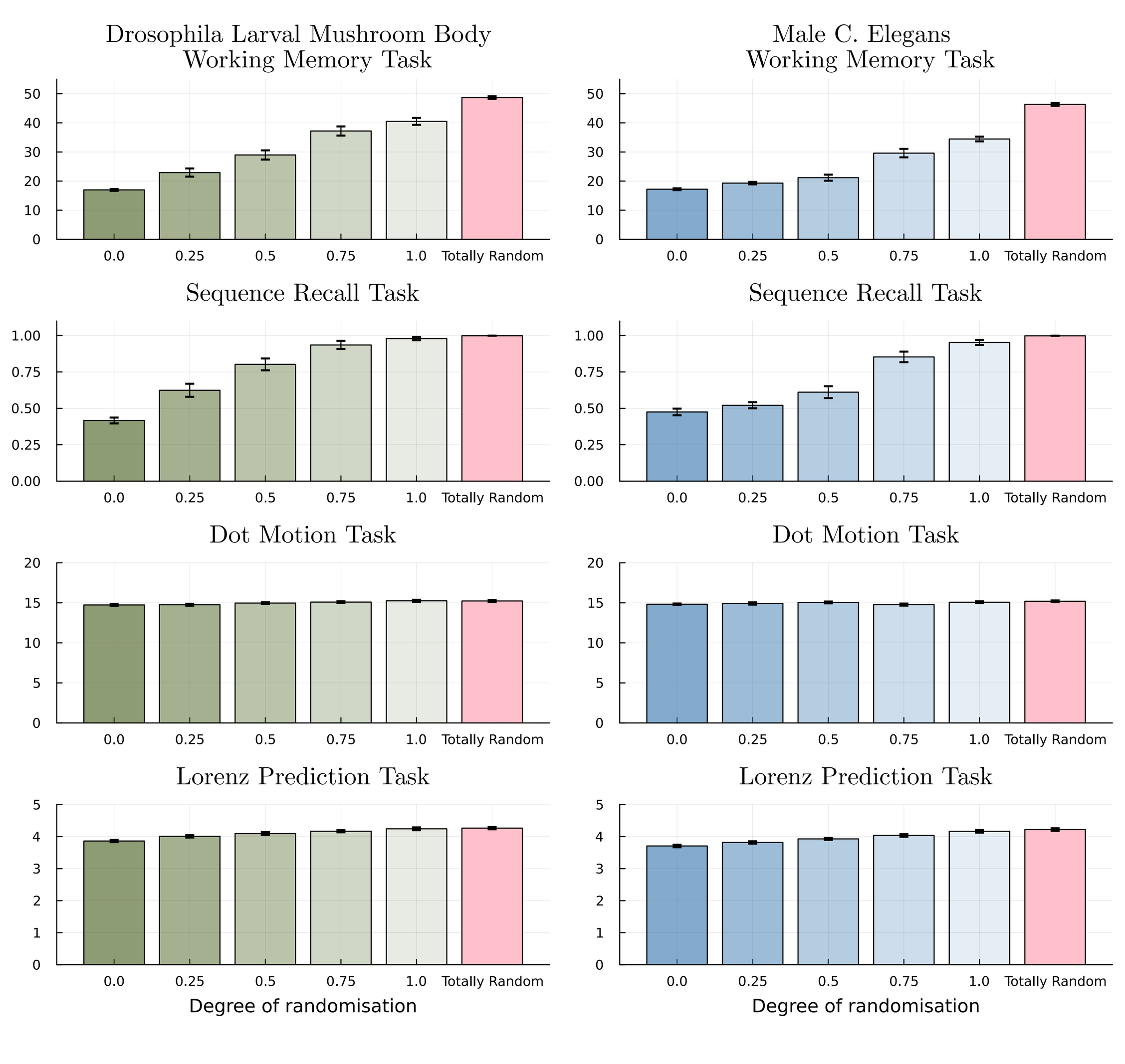

Figure 7. Task performance across different randomisation levels.

2. Results: Preserving Topology

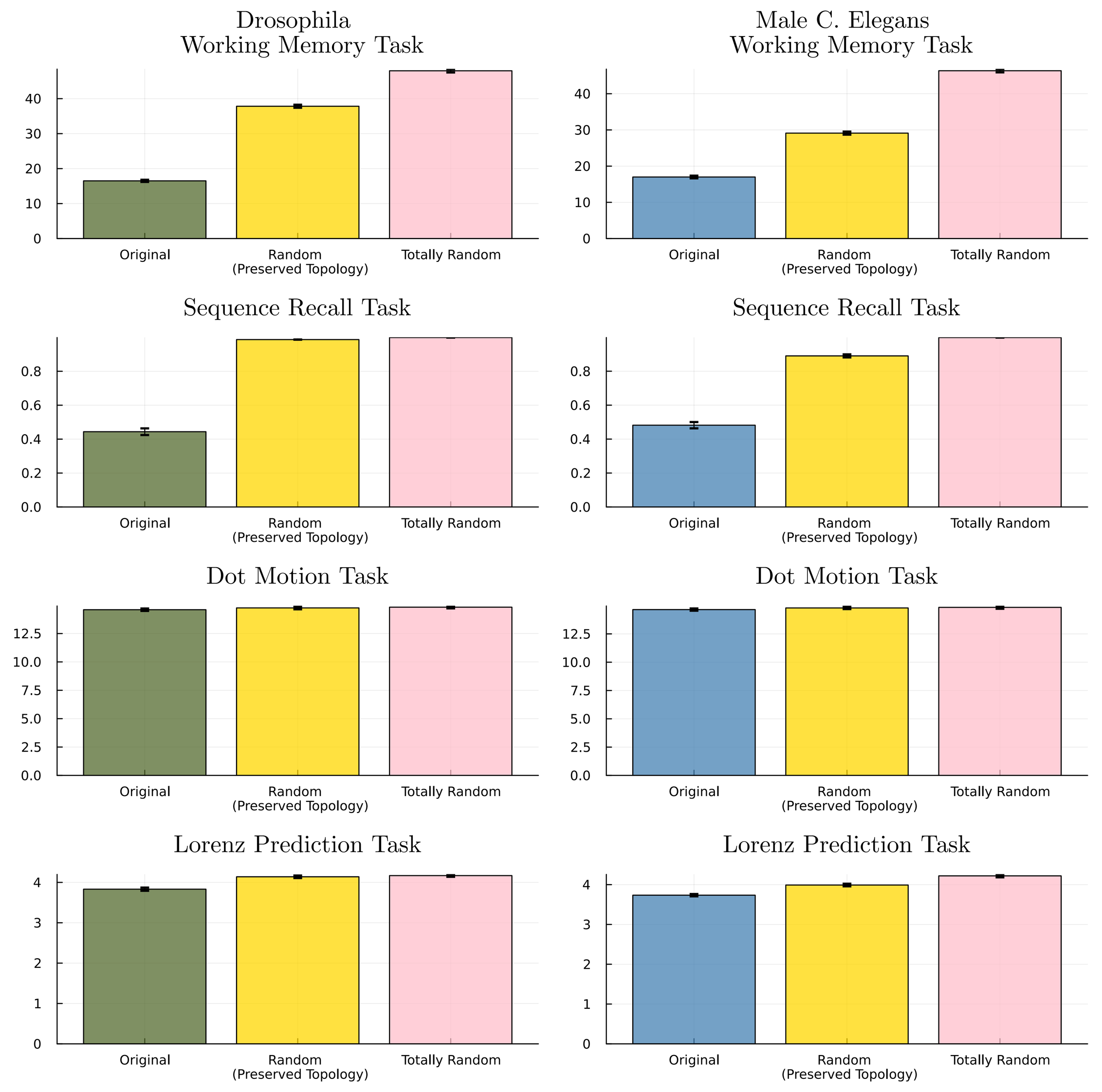

Figure 8. Performances across Original connectomes, Randomised with preserved topology, and Totally Random networks.

3. Results: Varying E-I Ratio

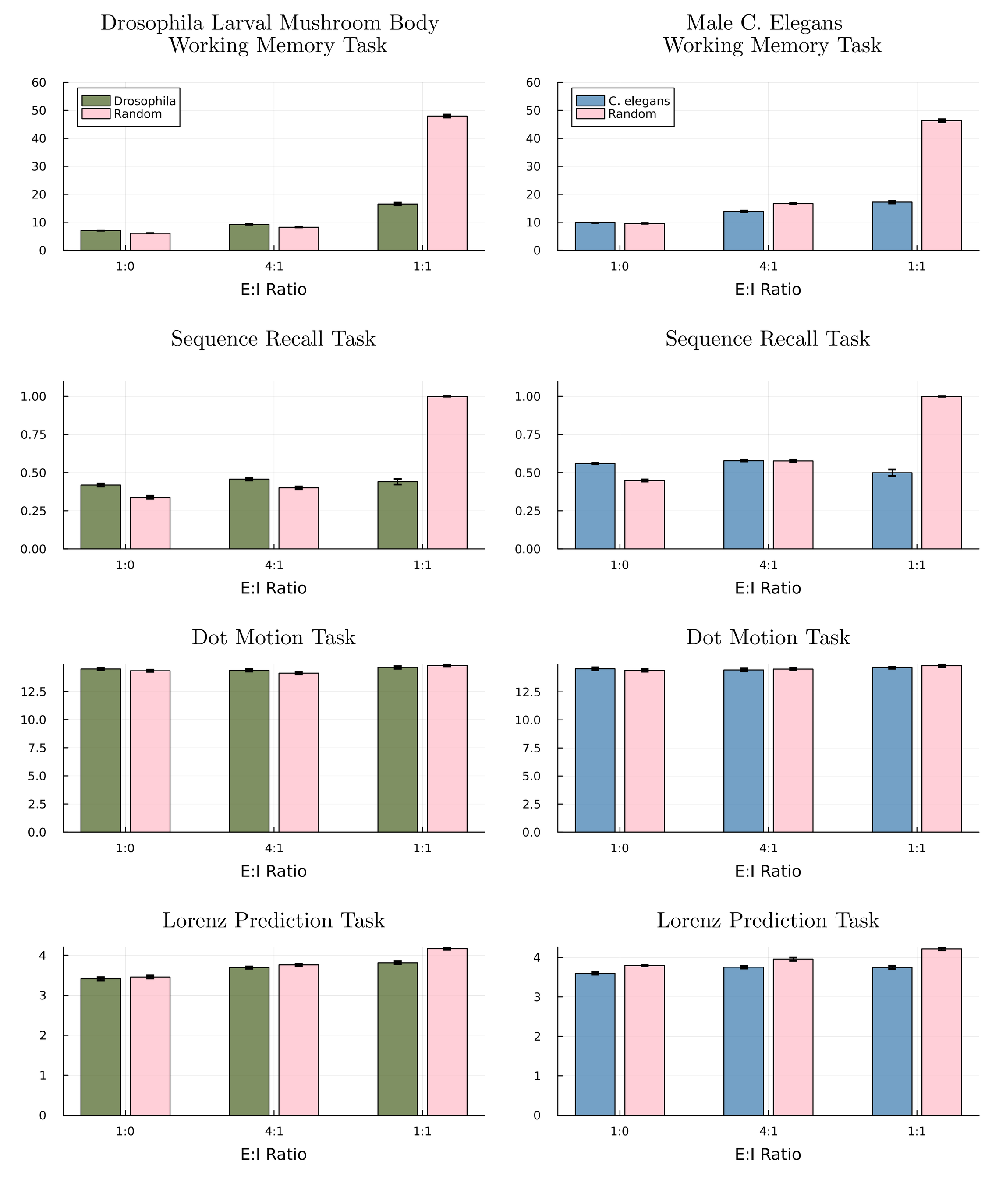

Figure 9. Performances of connectomes and random reservoirs across different E-I ratios.

Future Ideas

The connectomes used in this study may not be optimal for the tasks presented here; the use of alternative connectomes from different organisms and brain regions could give different results. The tasks used here are of general computational interest, but may not be particularly relevant for biological neural networks. Using alternative tasks might also give further interesting and differing outcomes.

Conclusions

This work demonstrates that reservoir computing is surprisingly robust across network architectures and tasks such as perceptual decision making and time-series prediction, and that **random networks** perform significantly better than some biological neural networks in two **memory-related tasks**. This may be related to richer dynamics of random reservoirs and their relation to the Echo State Property.

References

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