Biological Heterogeneity Is Necessary Under Continual Learning

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INTRODUCTION

Motivation

- Cognitive tasks need network level neuronal communication
- Artificial neural networks (ANN) effectively solve these tasks
- But their weights are frozen after learning [1]
- Biological synapse continuously undergo adaptation

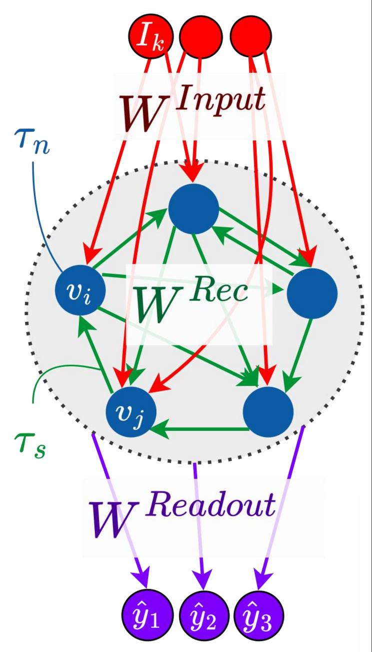
Open questions

- Can neural networks perform under continual learning?

METHODS

Network Specification

- A reservoir of rate neurons *(N = 100)*
- Random and sparse recurrent connectivity *(p = 0.1)*
- Sigmoidal activation function
- Synapses with Hebbian and homeostatic plasticity
- Allowed heterogeneity

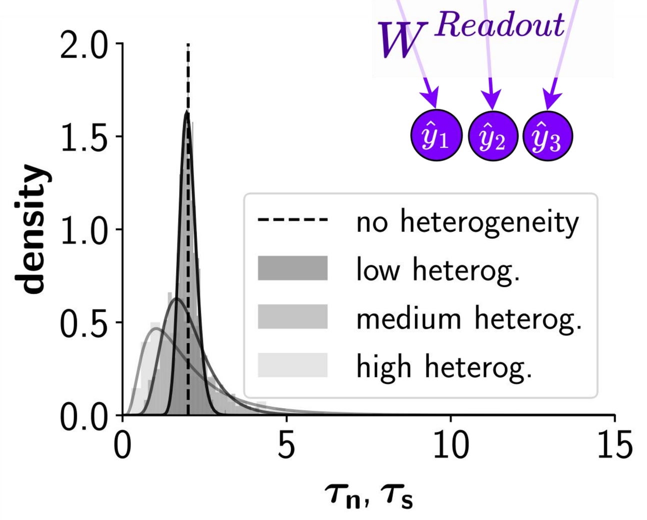


Dynamics

$$\tau_n \frac{dv_i}{dt} = -v_i + \sum_j W^{Rec}_{ij} f(v_j) + \sum_k W^{Input}_{ik} I_k$$

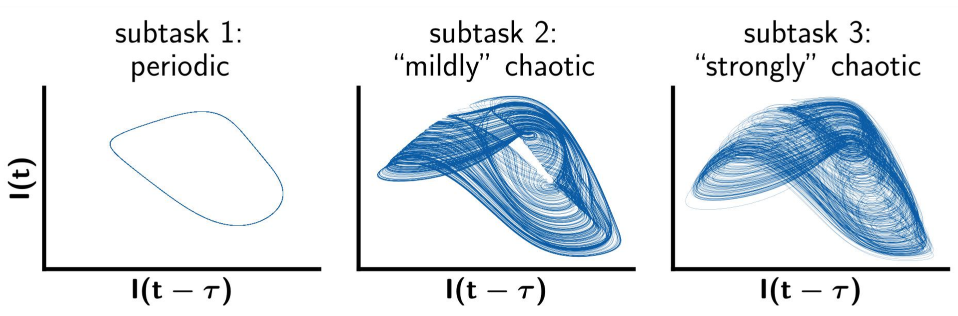
$$\tau_s \frac{dW^{Rec}_{ij}}{dt} = f(v_i) f(v_j) - \alpha W^{Rec}_{ij} f(v_j)^2$$

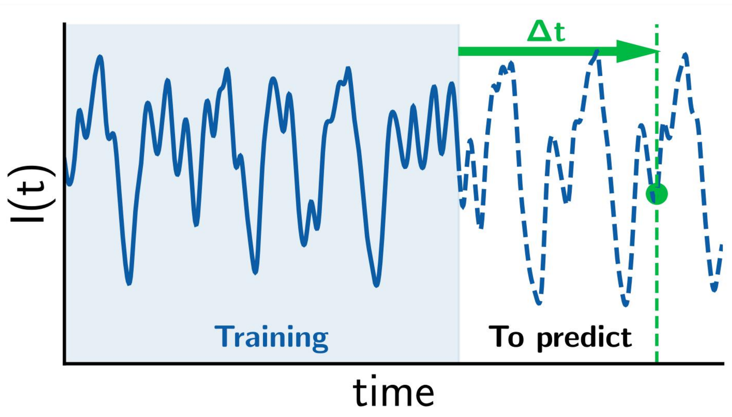
$$\hat{y} = W^{Readout} \cdot f(v)$$



Task

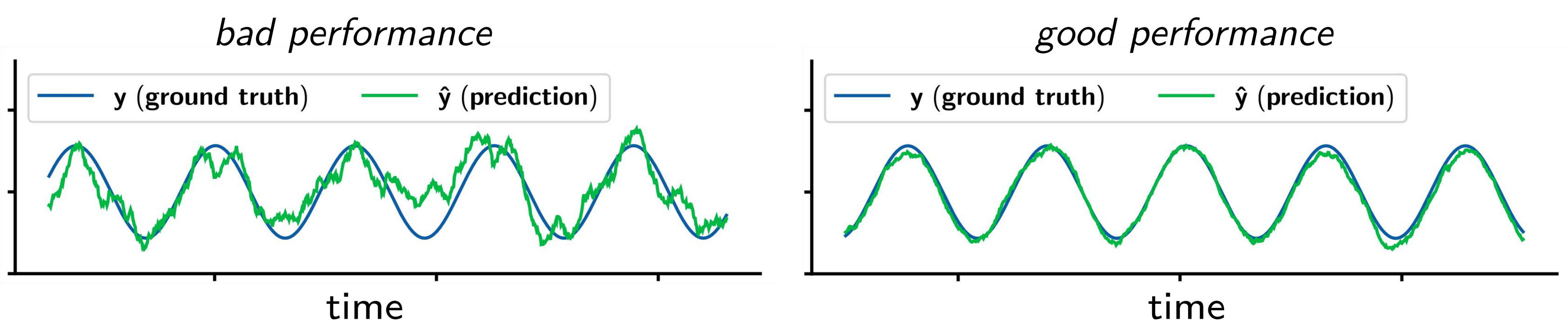
- Mackey-Glass time series prediction with three subtasks
- Near and distant future horizons (Δt) for each subtask
- Linear supervised readout





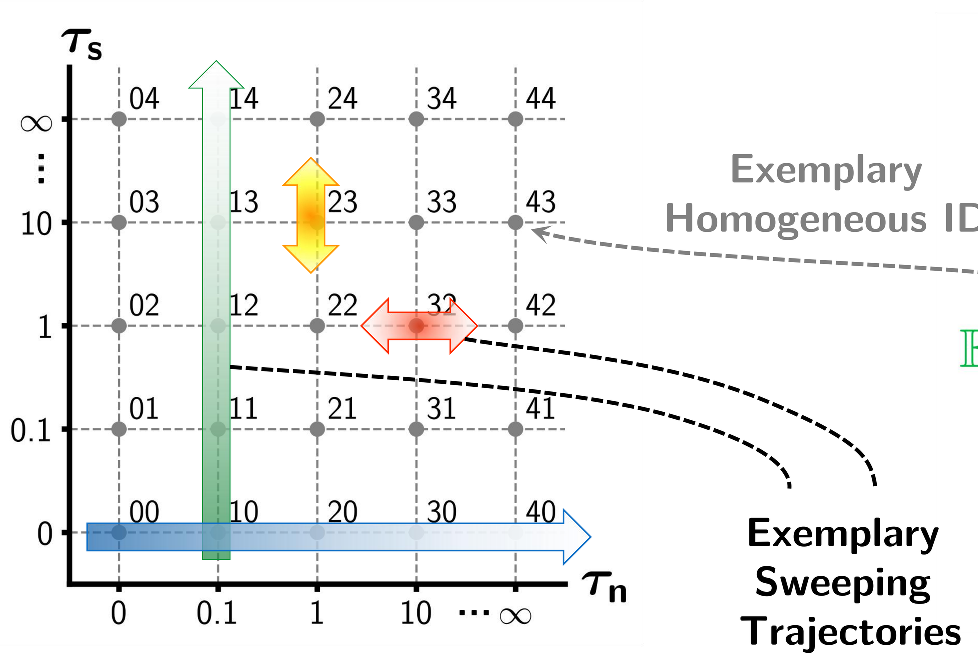
Performance measure

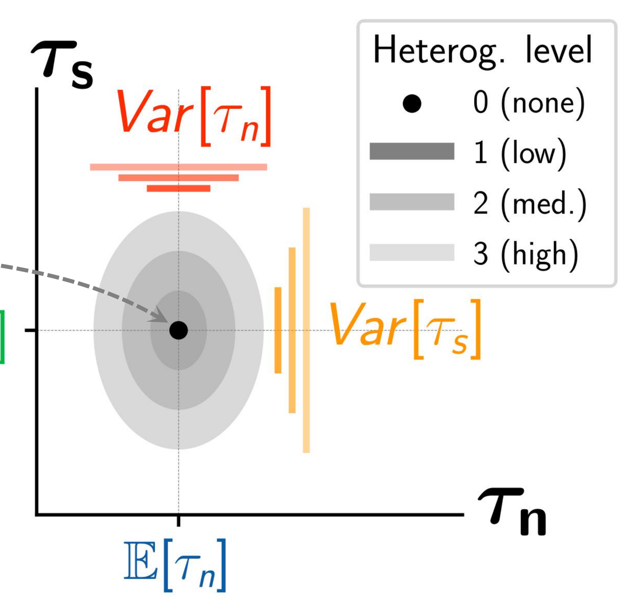
- Coefficient of determination $\quad R^2(\Delta t) = 1 - \frac{\langle (y(t) - \hat{y}(t;\,\Delta t))^2 \rangle}{\langle (y(t) - \langle y(t) \rangle)^2 \rangle}$
- Overall score on all horizons Δt $\quad \overline{R^2} = \frac{1}{M} \sum_{m=1}^{M} R^2(\Delta t_m)$



Parameters

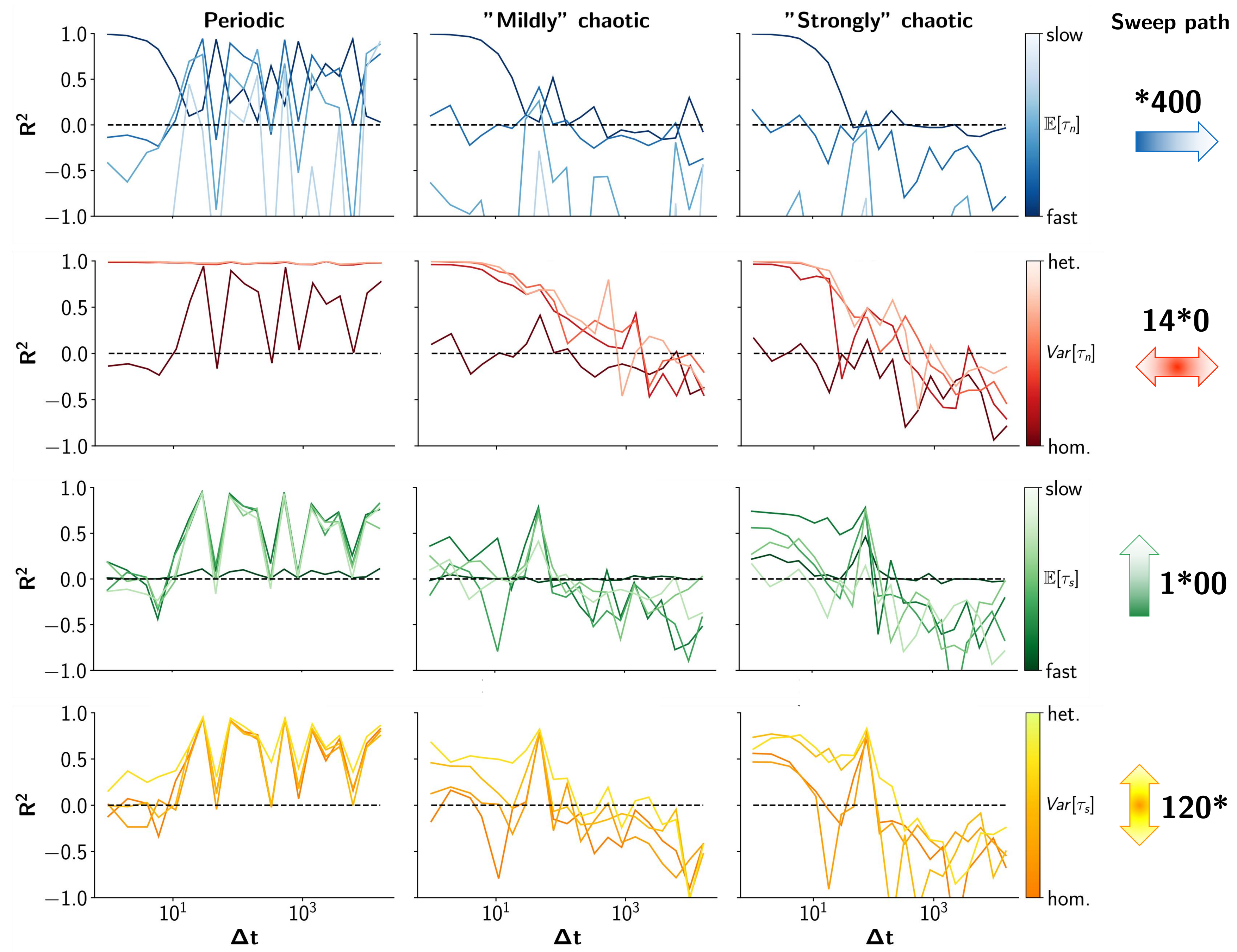
- Network ID: $\{E[\tau_n], E[\tau_s], Var[\tau_n], Var[\tau_s]\}$

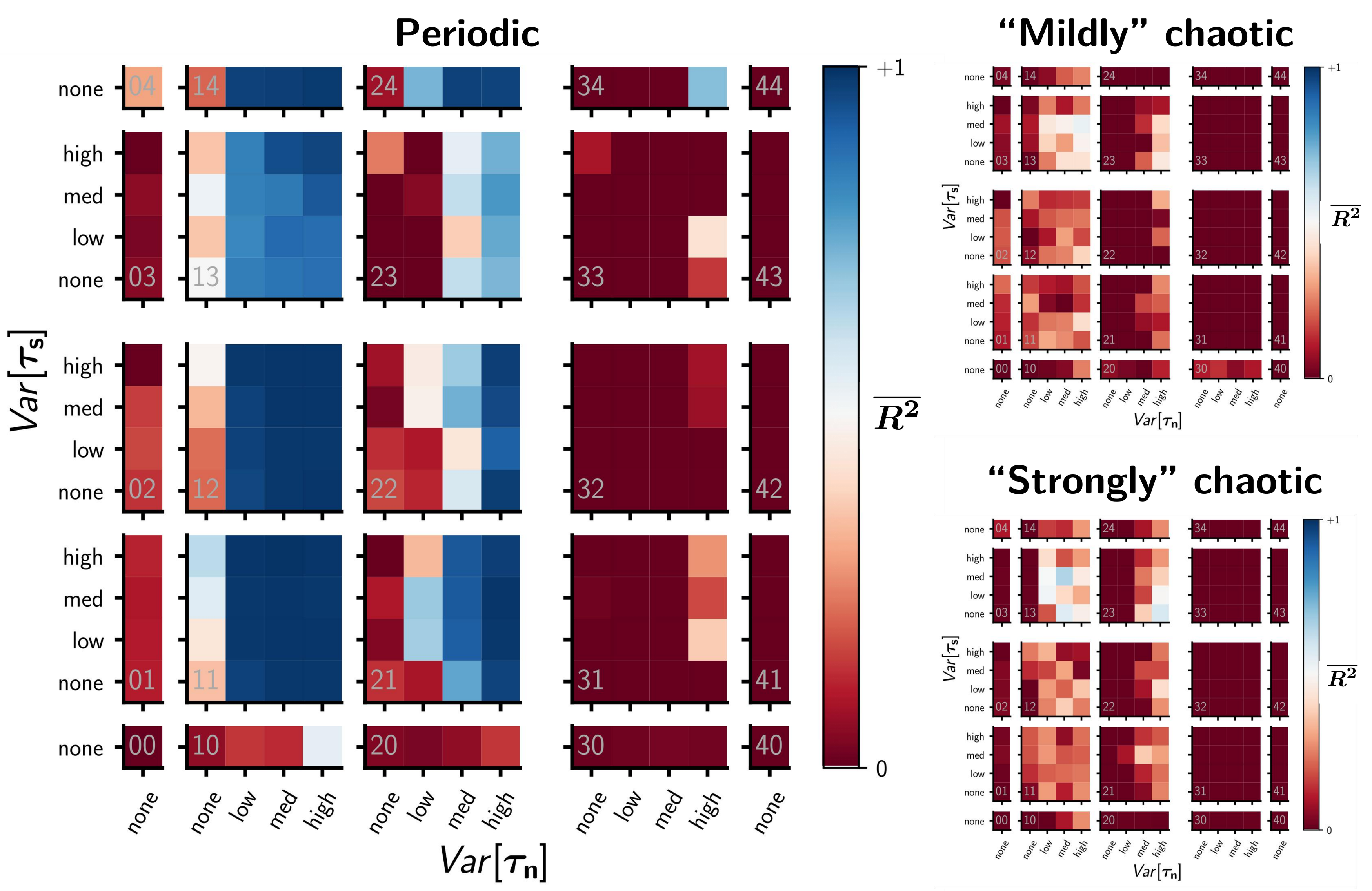




Neuronal sweep	***Synaptic sweep***
$Var[\tau_n] = Var[\tau_s] = 0$ $E[\tau_s] = const.$	$Var[\tau_n] = Var[\tau_s] = 0$ $E[\tau_n] = const.$
$E[\tau_n] = const.\ ;\ E[\tau_s] = const.$ $Var[\tau_s] = const.$	$E[\tau_n] = const.\ ;\ E[\tau_s] = const.$ $Var[\tau_n] = const.$
Neuronal heterogeneity sweep	***Synaptic heterogeneity sweep***

RESULTS





CONCLUSION

1. Continual learning does not hamper performance if neuronal and synaptic parameters are suitably distributed.
2. Diverse neuronal timescales help capture the main frequencies in periodic tasks, but they are not sufficient to capture the context in non-periodic tasks.
3. Synaptic heterogeneity provides a means to encode contexts of different lengths in the adaptive weights.
4. The best performance is achieved with some degree of synaptic and neuronal heterogeneity.
5. The optimal heterogeneity profile depends on the task.

OUTLOOK

In any network, there is a trade-off between memory and information processing capacity [2, 3]. Our next step is to quantify the effect of neuronal and synaptic heterogeneity on this trade-off by computing the change in the information processing capacities of different degrees.

References

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