Working memory facilitates reward-modulated Hebbian learning in recurrent neural networks

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Introduction

How do we learn new movements?

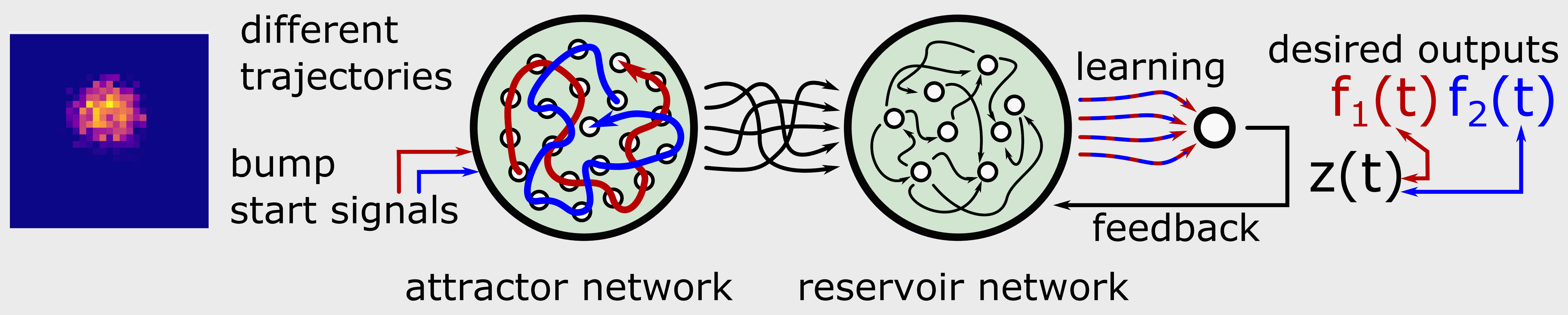
- reservoir computing model does that with a pool of randomly connected (cortical) neurons and plastic readout weights [1]
- training the readout with FORCE [1] is efficient but implausible
- training with plausible learning rules such as reward-modulated Hebbian learning [2] only works for short and simple tasks
- the key problem is that plausible rules are too unstable

Our model:

- we extend the reservoir with dynamic working memory
- the memory provides a temporally stable signal to make reward-modulated Hebbian learning more robust
- it is implemented with a 2D dynamic attractor [3]

Model

Attractor network (left) creates a task-specific trajectory and feeds it to the **reservoir network** (right), which learns the task:



Attractor network [3]. Rate neurons $\mathbf{x}$ with input $\mathbf{e}$ and adaptation $\mathbf{h}$ of strength s:

$$\tau_{\mathrm{m}}\dot{\mathbf{x}} = -\mathbf{x} + [\mathbf{Jx} + \mathbf{e} - \mathbf{h}]_+$$
$$\tau_{\mathrm{a}}\dot{\mathbf{h}} = -\mathbf{h} + s\,\mathbf{x}$$

- weights $\mathbf{J}$ create a "bump" solution
- adaptation $\mathbf{h}$ moves the bump
- this movement projects to the reservoir

Reservoir network [1, 2]. Rate neurons $\mathbf{u}$ with input $\mathbf{W}_{\mathrm{attr}}\mathbf{x}$, readout $\mathbf{z}$ and noise $\boldsymbol{\mu}$:

$$\tau\dot{\mathbf{u}} = -\mathbf{u} + \mathbf{W}_{\mathrm{rec}}\tanh(\mathbf{u}) + \mathbf{W}_{\mathrm{fb}}\mathbf{z} + \mathbf{W}_{\mathrm{attr}}\mathbf{x}$$
$$\mathbf{z} = \mathbf{W}_{\mathrm{ro}}\tanh(\mathbf{u}) + \boldsymbol{\eta}$$

- the task is to approximate $\mathbf{f}(t)$ with $\mathbf{z}(t)$
- attractor input is task-specific
- only readout weights $\mathbf{W}_{\mathrm{ro}}$ are plastic

Reward-modulated Hebbian rule [2]:

$$\Delta\mathbf{W}_{\mathrm{ro}}(t) = \eta(t)M(t)(\mathbf{z}(t) - \bar{\mathbf{z}}(t))\mathbf{r}^{\top}(t), \quad \eta(t) = \eta_0/(1 + t/\tau_\eta)$$

where $\bar{x}$ denotes low-pass filtered x ($\Rightarrow \mathbf{z}(t) - \bar{\mathbf{z}}(t) \approx \boldsymbol{\eta}(t)$). Reward modulation $M(t)$ is **binary** and tracks performance $P(t)$ with the Heaviside step function Θ as:

$$M(t) = \Theta(P(t) - \bar{P}(t)), \quad P(t) = -\|\mathbf{f}(t) - \mathbf{z}(t)\|^2$$

Conclusions

Key results

- attractor input makes reward-modulated Hebbian rule faster and more robust
- it works on harder and longer tasks, when the pure reservoir network fails completely
- it also works when weight updates are applied at the end of each training period
- attractor network exhibits a set of stable, task-specific trajectories without learning
- those trajectories are diverse enough to learn multiple tasks with the same readout weights

Possible extensions

- attractor network can be combined with a transient input signal to decouple the "elapsed time" input (attractor) and the task-specific input

Experimental setup

Short and long tasks:

- 1D functions sampled from a Gaussian Process (matching the complexity of the few hand-picked tasks from [1, 2])
- 50 different tasks for each length, each for a new reservoir network (examples below)
- performance is measured with normalized cross-correlation (1 is the perfect match)

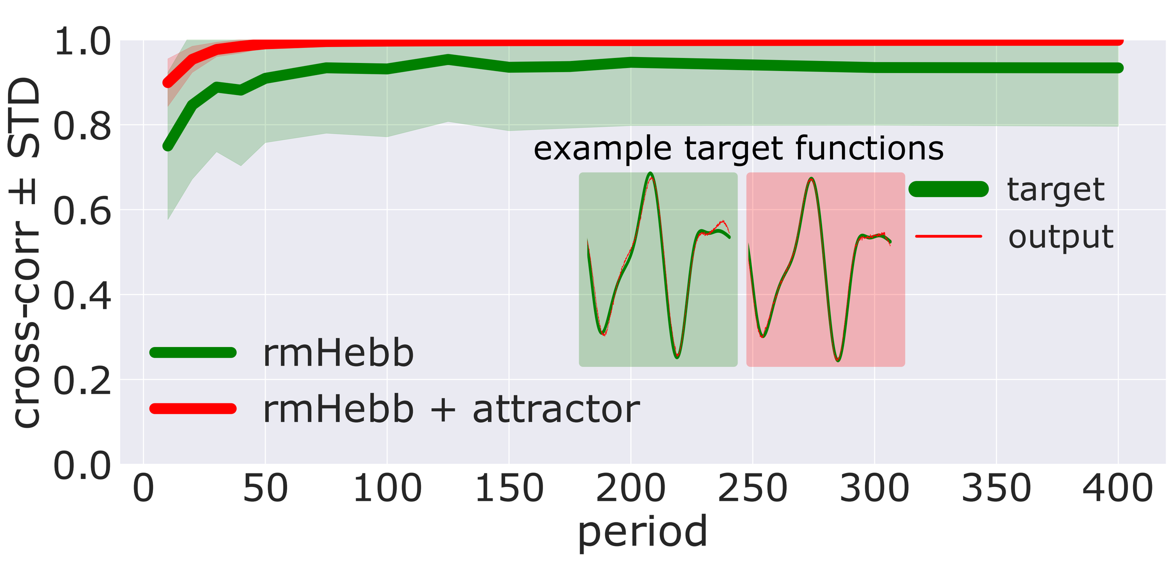
Digits task:

- 2D 1 second drawings of digits
- the attractor produces trajectories based on 50 similar inputs for each digit on train, and 50 on test

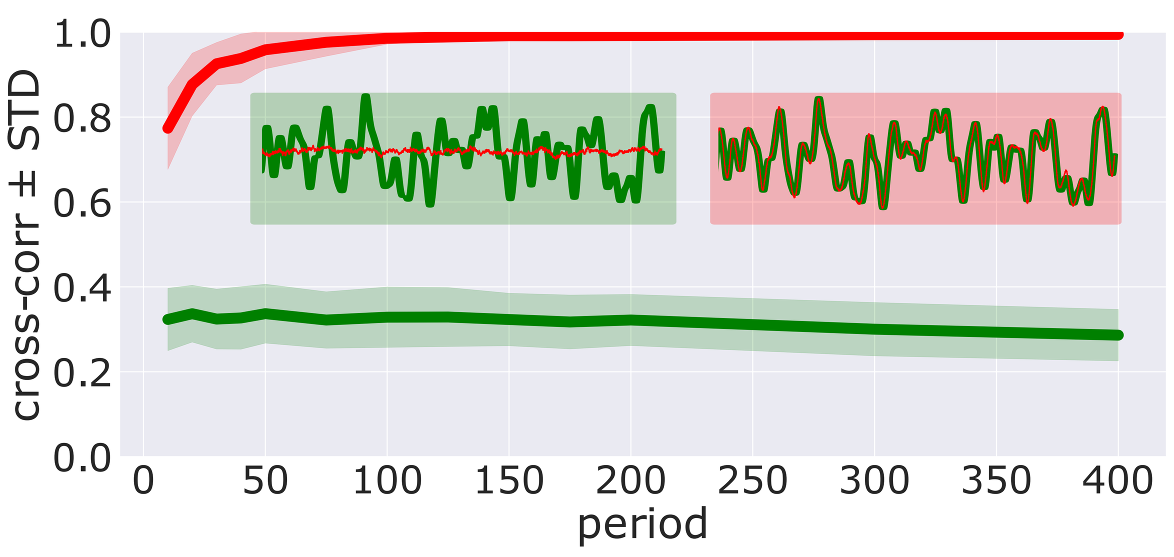
Simulation details:

- 2500 attractor neurons, 1000 reservoir neurons
- attractor networks is similar to [3], reservoir network matches [2]
- reservoir receives the same attractor input on each period (expect for the digits task)

Performance on short and long tasks



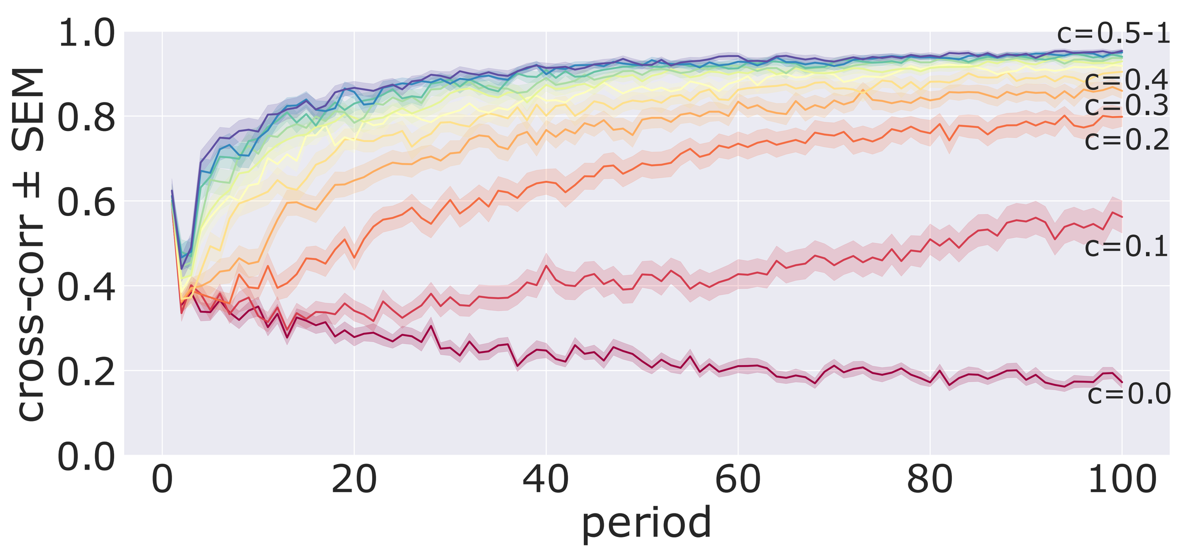
Mean performance on **1 second** tasks and an example task (insets).



Mean performance on **10 seconds** tasks and an example task (insets).

- on short **1 second** tasks attractor input makes the reward-modulated Hebbian rule (**rmHebb**) learn faster and better, reaching nearly perfect performance
- on longer **10 seconds** tasks, the reservoir alone fails completely, while our model just takes more trials to master each task
- same performance on the hand-picked functions from [1, 2]; perfect performance with FORCE

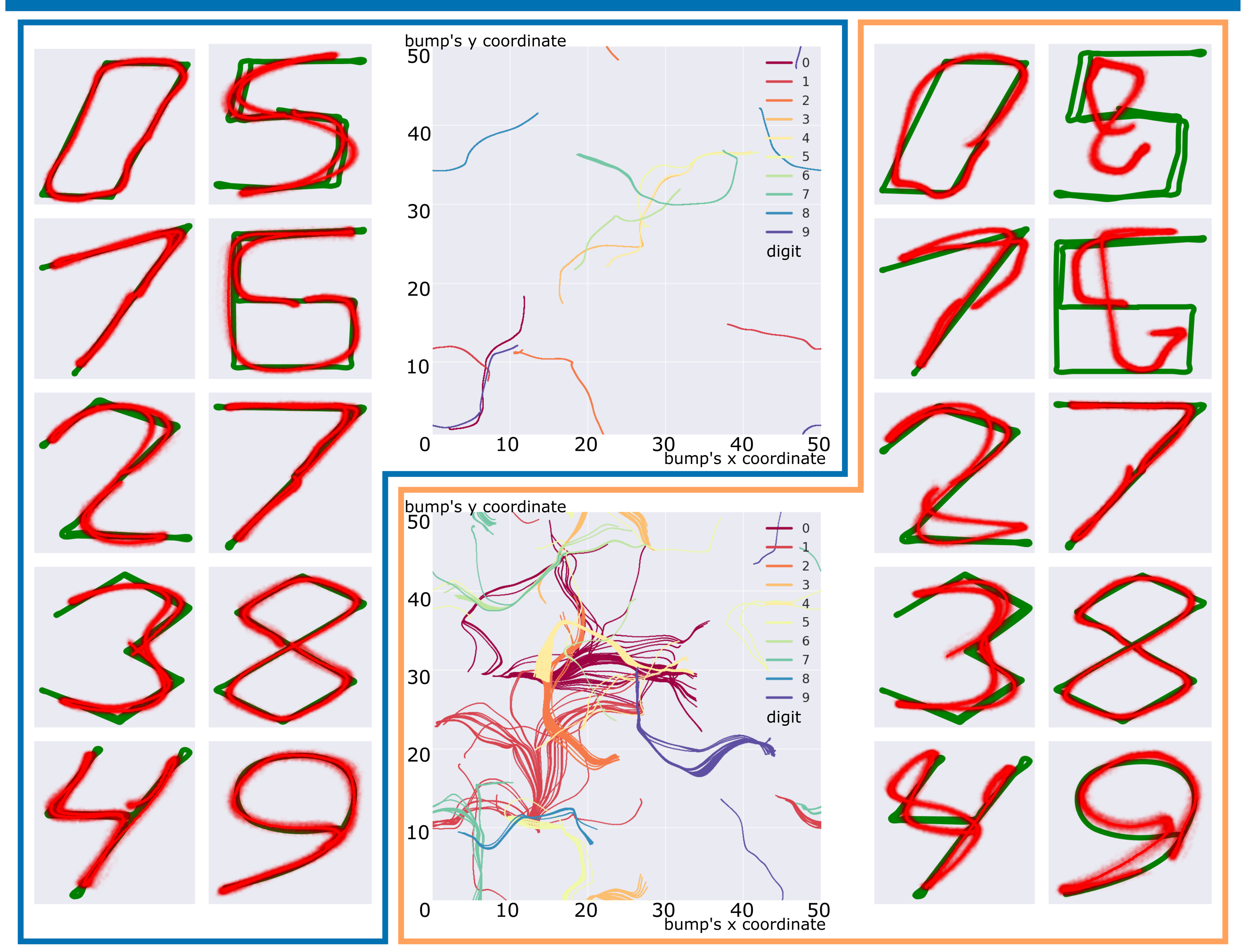
Delayed updates on short tasks



Mean performance with delayed updates on 1 second tasks for different attractor coupling $c = [0, 1]$.

- weight updates are summed in the background and only applied after each 1 second period
- for strong coupling with the attractor c (the reservoir receives $c\mathbf{W}_{\mathrm{attr}}\mathbf{x}$), performance is still high

Learning of multiple signals (the digits task)



Targets (green) and outputs (red) with **noiseless** (left) and **noisy** (right) attractor trajectories, as learned by a single set of readout weights. FORCE with noisy input performed as well as the reward-modulated Hebbian rule

Contact information & acknowledgments

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