

## Meta-learning Hebbian plasticity for continual familiarity detection

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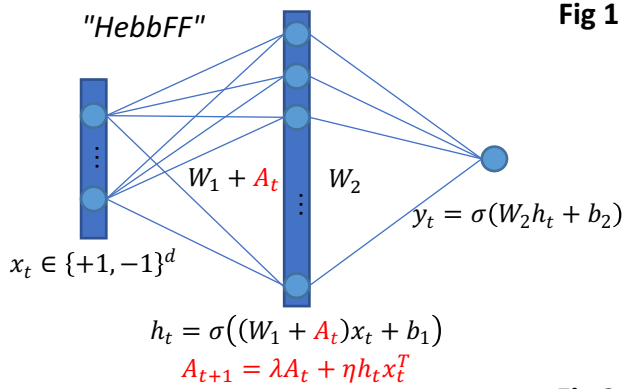
Memories are stored and recalled throughout the lifetime of an animal, but many models of memory, including previous models of familiarity detection, do not operate in a continuous manner. We consider a family of models that recognize previously experienced stimuli and, importantly, operate and learn continuously. Specifically, we investigate a learning paradigm in which stimuli are presented in a *streaming* fashion with repetitions at various intervals, and the subject/model must report whether the current stimulus has previously appeared in the stream. We propose a feedforward network architecture with ongoing plasticity in the synaptic weight matrix. Parameters governing plasticity and static network parameters are meta-learned using gradient descent to optimize the continual familiarity detection process. This architecture, unlike recurrent networks without ongoing plasticity, generalizes easily over a range of repeat intervals even if trained with a single interval. We show that an *anti*-Hebbian plasticity rule (co-activated neurons cause synaptic *depression*) enables repeat detection over much longer intervals than a Hebbian one, and this is the solution most readily found by meta-learning. This rule leads to experimentally observed features such as repeat suppression in the hidden layer neurons. In contrast to previous theoretical work, the capacity of these networks remains constant across their lifetimes, meaning that pairs of stimuli with a given temporal separation are stored and recognized as familiar independent of the network's input history. We also consider learning rules that use an external gating circuit to control plasticity. Collectively, these models demonstrate a range of different psychometric curves that we compare to human performance.

**Additional Detail.** Every day, a continual stream of sensory information causes lasting synaptic changes in our brains that alter our responses to future stimuli. Two critical unsolved problems regarding memory are (i) how local synaptic updates enable distributed storage and global readout of information, and (ii) how these updates support the continual storage of information without "catastrophic forgetting," in which the network either erases previous memories [1] or renders stored information unreadable [2]. To investigate these questions, we consider an ongoing repeat detection task that requires both of these features and propose network models that successfully implement them, with relevance for results from the perirhinal [3] and inferotemporal cortices [4]. The network receives a stream of  $d$ -dimensional random binary inputs  $x_t \in \{+1, -1\}^d$ . With probability  $p$ , the stimulus at time step  $t$  may be a copy of the stimulus presented at times step  $t-R$  ( $P(x_t = x_{t-R}) = p$  for all  $t \geq R$ ), or with probability  $1 - p$  it may be a novel stimulus. The output of the network should be  $y_t = 0$  if  $x_t$  is novel and  $y_t = 1$  if it appeared previously.

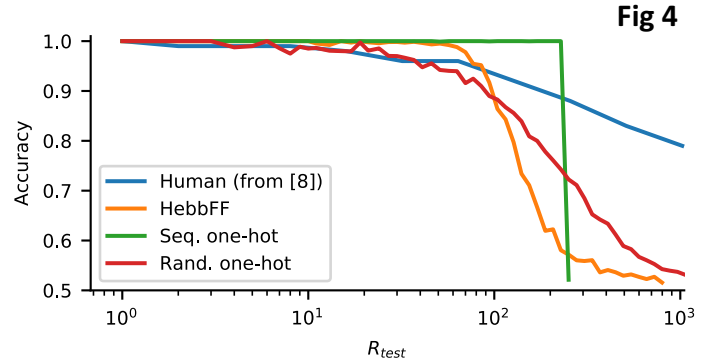
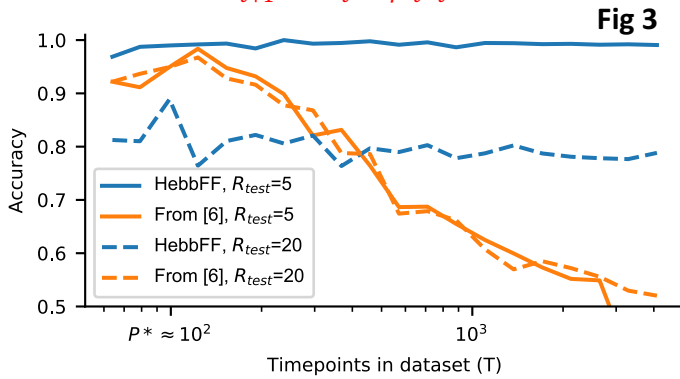
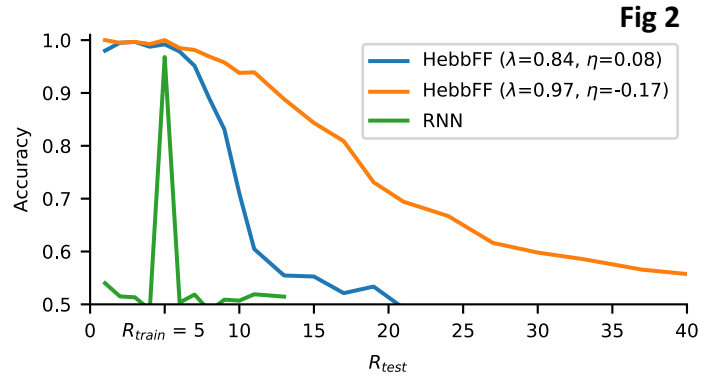
We use a feedforward network with a single hidden layer and the addition of activity-dependent ongoing Hebbian plasticity ("HebbFF") (**Fig 1**). Given input  $x_t$  at time  $t$ , the hidden layer is activated as  $h_t = \sigma((W_1 + A_t)x_t + b_1)$  and read out as  $y_t = \sigma(W_2 h_t + b_2)$ .  $A_t$  is the "plastic" matrix, updated at every time step according to  $A_{t+1} = \lambda A_t + \eta h_t x_t^T$ . We use backpropagation through time as a form of meta-learning to find the optimal parameters  $W_1, b_1, W_2, b_2, \lambda, \eta$ .

HebbFF stores its input history in the plastic synaptic matrix  $A_t$  unlike an RNN, which uses ongoing activity. The HebbFF architecture both solves the task and shows good generalization. In contrast, an RNN trained on a single dataset with  $T=500$  timepoints and a fixed repeat interval  $R=5$ , fails to generalize to new datasets (it learns a classifier rather than the recognition task). If we train an RNN with "infinite" data by generating a new dataset for every iteration of backpropagation, the RNN generalizes across datasets, but fails to generalize across values of  $R$  (**Fig 2**). In contrast, HebbFF generalizes not only to a new dataset with the same  $R$ , but also to datasets with smaller or even somewhat larger  $R$ 's (**Fig 2**).

After training successfully converges, HebbFF most commonly learns a *negative* value for  $\eta$ , corresponding to an *anti*-Hebbian plasticity rule. While it is possible to coerce the network to learn a Hebbian rule ( $\eta > 0$ ), generalization across  $R$ 's is much worse (**Fig 2**) and training takes longer. As a



**Fig 1**



result of the anti-Hebbian rule, when a familiar stimulus is presented, the hidden unit activation is low since the synapses storing that stimulus are depressed. This is consistent with experimental results of repetition suppression [5], where a neuron's response decreases with repeated presentations of a stimulus. A Hebbian rule produces the opposite property.

In contrast to previous work showing impressive memory capacity [6], this network solves the task of *continual* learning. Its performance is independent of the length of the dataset  $T$ , and it can operate continuously without a need to "reset" the synaptic weights (**Fig 3**). In classic studies of recognition memory [7] subjects are presented an entire dataset and later asked to identify which stimulus is familiar in a two-alternative-forced-choice (2AFC) test. While the capacity for the 2AFC task in humans is on the order of thousands, it is much lower for continual repeat detection tasks [8] like the one we trained our networks to perform. This is consistent with the difference between critical capacity from [6] ( $P^* \approx 100$  in **Fig 3**) and our "repeat interval" capacity ( $R_{max} \approx 10$  for HebbFF in **Fig 3**).

To investigate the optimality of this architecture and compare with human performance, we also consider a more general plasticity rule in which  $A_t$  is updated by an external gating circuit with activations  $g_t$ . Synapses of the hidden units are overwritten by the synaptic update  $A_{t+1}^{ij} = g_t^i x_t^j$ , where  $g_t$  is a one-hot vector with the active unit chosen either randomly  $i = \text{rand}\{1..N_h\}$ , or sequentially  $i = t \pmod{N_h}$ . All the models can match human performance up to the point where mistakes begin ( $R \approx 64$ ), and the random model best resembles the gradual fall off in performance exhibited by humans, although with a more rapid decay (**Fig 4**). Investigation of this phenomenon remains for future work.

[1] Kirkpatrick et al., Proc. Natl. Acad. Sci. 114, 3521 (2017). [2] Gardner and Derrida, J. Phys. Math. Gen. 21, 271 (1988). [3] Brown and Aggleton, Nat. Rev. Neurosci. 2, 51 (2001). [4] Meyer and Rust, eLife 7, (2018). [5] Xiang and Brown, Neuropharmacology 37, 657 (1998). [6] Bogacz and Brown, Hippocampus 13, 494 (2003). [7] Standing, Q. J. Exp. Psychol. 25, 207 (1973). [8] Brady et al., Proc. Natl. Acad. Sci. 105, 14325 (2008).