

1 **Reviewer 1** asked if the weights are effectively learning to relax to the same steady state from random initial conditions.
 2 We performed an analysis to be added to the appendix (Fig. 1a,b), which shows that for two different runs the weights
 3 start being perpendicular –since randomly initialised– and thereafter the n -dimensional angle between the weights is not
 4 zero. Thus the weights are not effectively relaxing to a fixed set of values but rather change based on the environmental
 5 input. Additionally, the absolute weights of a particular network keep changing as well (Fig. 1c)

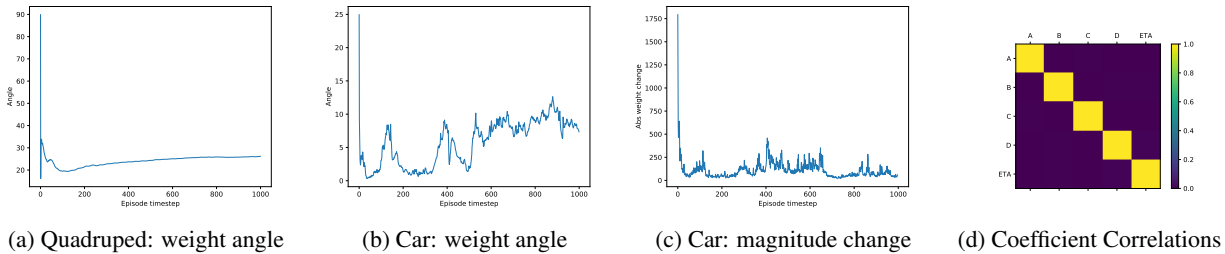


Figure 1

6 Following **Reviewer 1**'s suggestion of having both the initial condition and plasticity rules optimized, we performed
 7 6 evolutionary runs in the car-racing environment; 3 of them converged to high-performance solutions (879 ± 69),
 8 and 3 of them did not (13 ± 2). This suggest that evolving both at the same time could be more challenging (all
 9 random+Hebbian runs always found a high-performing solution). We are currently running the same experiments for
 10 the ant, but they are unfortunately not finished yet.

11 **Reviewer 2** noted that "it would be quite interesting if the authors could expand more their analysis of the evolved
 12 plasticity rules." We performed a correlation analysis of the evolved Hebbian coefficients and found no correlation
 13 between them –neither Pearson's r nor Spearman's ρ –, suggesting that the coefficients are independent with no obvious
 14 internal structure in the learning rules (Fig. 1d). We are currently investigating if frequent pattern mining methods (e.g.
 15 apriori algorithm) could reveal additional insights.

16 **Reviewer 3** said to "find it difficult to relate the Hebbian plasticity rules that are considered in this paper to rules for
 17 synaptic plasticity in the brain that have been found in neuroscience" arguing that "synaptic plasticity in the brain
 18 appears to rely often on a multitude of gating signals, and on the relative timing of pre- and postsynaptic activity." The
 19 most studied plasticity mechanism in neuroscience is spike-timing-dependent plasticity (STDP). However, STDP isn't
 20 the only plasticity mechanism that has been observed in the brain.

21 NNs with continuous outputs are usually interpreted as an abstraction of spiking neural networks in which the continuous
 22 output of each neuron represents a *spike-rate coding* average (instead of spike-timing coding) of a neuron over a long
 23 time window or, equivalent, of a subset of spiking neurons over a short time window (in this scenario, the relative timing
 24 of the pre and post-synaptic activity doesn't play a central role anymore ¹. Spike-rate-dependent plasticity (SRDP) is
 25 well documented phenomena in biological brains ^{2 3}. That being said, our goal is not to provide a detailed model of
 26 plasticity mechanisms in biological brains, but rather to demonstrate that evolved local rules can show adaptability and
 27 yield competitive results. Additionally, in contrast to earlier work that restricted learning rules to only four different
 28 hand-designed types (ref [30]), we evolve arbitrary synapse-specific Hebbian rules.

29 **Reviewer 4** objected to the claim that the Hebbian approach led to greater generalization due to the fact the system was
 30 optimized for all the morphologies. Following this fair critique, we launched a new set of experiments where one of the
 31 damaged morphologies was left out during training. While the static network only managed to solve the morphologies
 32 it had seen during the training phase, the Hebbian network –to our surprise– managed to solve all three of them in each
 33 of 3 different evolutionary runs. On the unseen morphology the Hebbian approach reached a performance of 471 ± 87
 34 compared to the static-network performance of 31 ± 46 . We believe that this adaptation to the unseen morphological
 35 changes provides evidence of greater generalisation for the Hebbian network in relation to the static-weights one.

36 We ran an ablation where the Hebbian parameters are shared among neurons in one layer for the car environment: all 3
 37 evolutionary runs resulted in poor performance (max reward 13 ± 2 as opposed to 870 ± 13 with individual learning
 38 rules). This suggests that a higher number of parameters is important for the agents to adapt. **Reviewer 4** argued that
 39 due to the rotational symmetry of the ant, the under-performing runs shouldn't always be the same morphology: the
 40 reported results are averages across 100 rollouts of the best solution, which had visibly evolved to favour one of the
 41 damaged morphologies; in other evolutionary trains the favoured morphology changed, which we will clarify in the
 42 paper. We finally thank the reviewers for their careful read and will subsequently correct the equation after line 149.

¹Brette, 2015. *Philosophy of the Spike: Rate-Based vs. Spike-Based Theories of the Brain*. Frontiers in Systems Neuroscience

²Sjöström et al., 2001. *Rate, timing, and cooperativity jointly determine cortical synaptic plasticity*. Neuron

³Prescott et al., 2008. *Spike-Rate Coding and Spike-Time Coding*. Journal of Neuroscience