Optimal percentage of inhibitory synapses in multi-task learning

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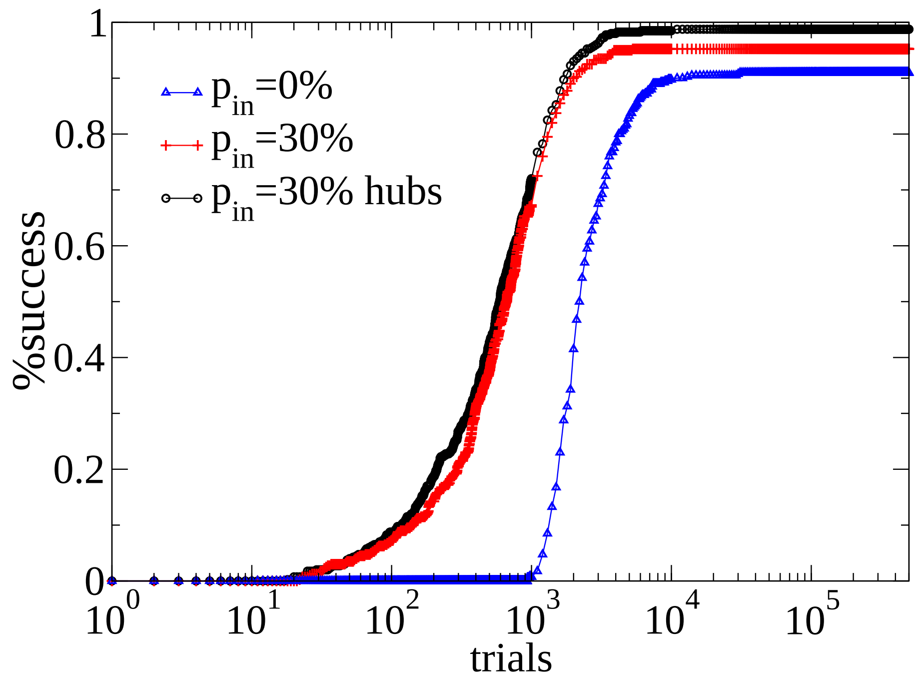
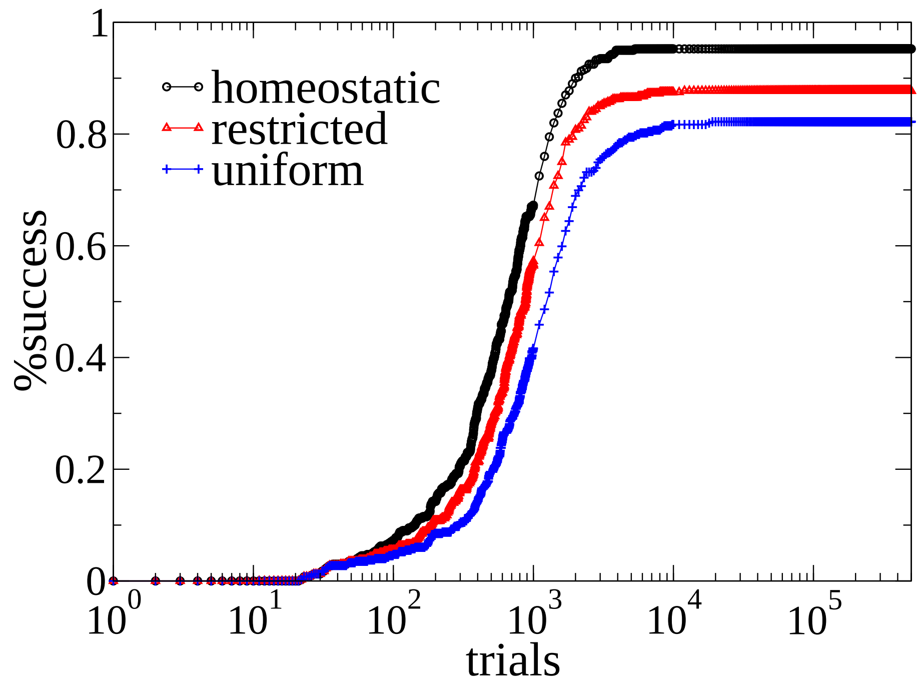
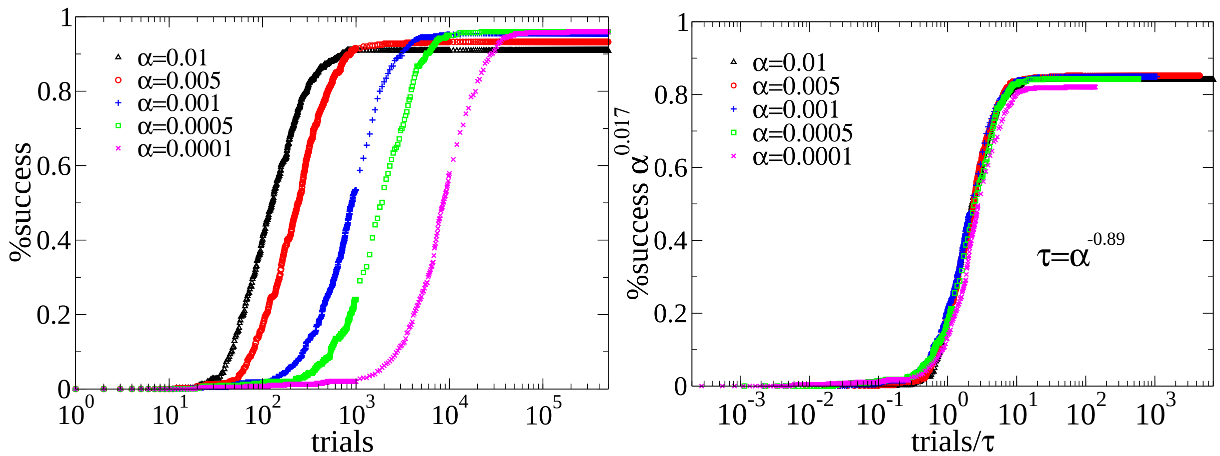


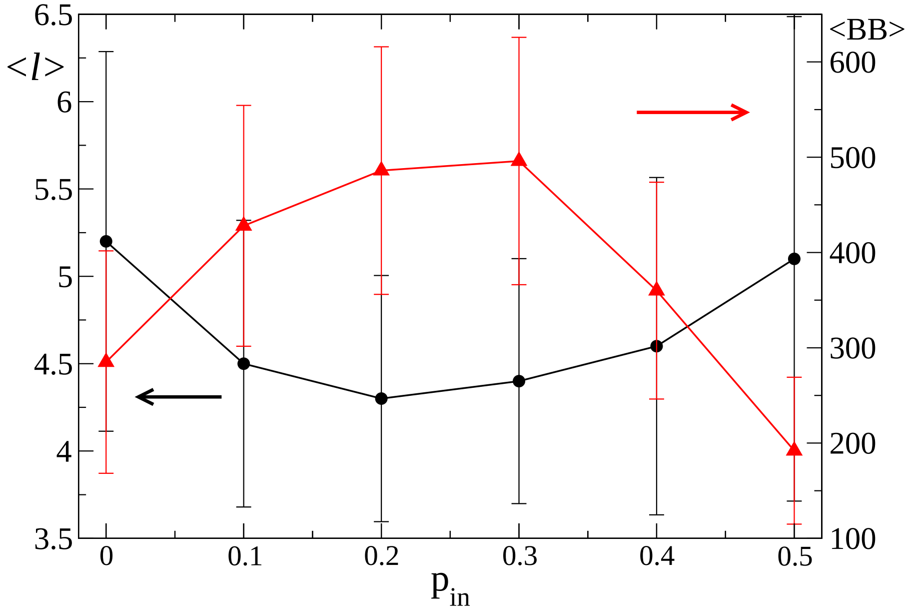
Supplementary Figure 1. Percentage of networks giving the right answer to the XOR rule as a function of the number of times the rule is applied for 500 configurations with $N = 250$ neurons ($k_d = 3$, $\alpha = 0.001$, homeostatic plasticity). Three different cases are analysed: purely excitatory networks, networks with $p_{in} = 30\%$ inhibitory synapses with random connectivity degree and networks where inhibitory synapses are assigned to random neurons with $k_{out} > 10$. The best performance is obtained for inhibitory neurons highly connected also for different plastic adaptations. The same behaviour is observed also for other rules and other values of $p_{in} > 0$.



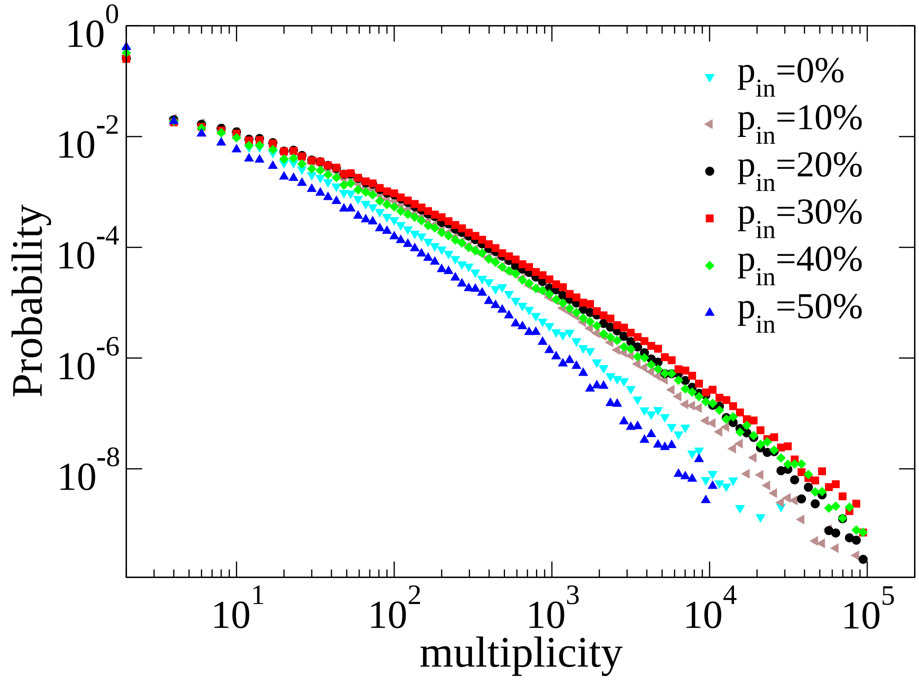
Supplementary Figure 2. Percentage of networks giving the right answer to the XOR rule as a function of the number of times the rule is applied for 500 configurations with $N = 250$ neurons ($k_d = 3$, $\alpha = 0.001$, $p_{in} = 0.3$ no hubs). Three different plastic adaptations are analysed: Uniform (all active synapses undergo the same modification independently of their excitatory/inhibitor character), restricted (only excitatory synapses are modified), homeostatic (excitatory and inhibitory synapses undergo modifications with opposite sign). The best performance is obtained for homeostatic plasticity, also for different p_{in} and hub inhibitory neurons. The same behaviour is observed also for the other rules.



Supplementary Figure 3. Left: Percentage of networks giving the right answer to the parallel learning of XOR and AND rules as a function of the number of times the rule is applied for 500 configurations of networks with $N = 250$ neurons and different α ($k_d = 3$, $p_{in} = 0.3$). The average learning time τ increases for decreasing α, as $\tau \sim \alpha^{-0.89}$, whereas the best performance increases for slow plastic adaptations, as $\sim \alpha^{-0.017}$. Right: Universal learning curve obtained by rescaling the axes according to $S = \alpha^{-0.017} f(t/\tau)$. The scaling relations obtained for single rule learning are $\tau \sim \alpha^{-1}$ and $S = \alpha^{-0.05} f(t/\tau)$.



Supplementary Figure 4. The average number of neurons involved in avalanches giving the right answer to, both, the AND and XOR rules, $< BB >$, for 500 configurations of networks with $N = 1000$ neurons and different percentages of inhibitory synapses ($k_d = 3$, $\alpha = 0.001$). The maximum value is detected for p_{in} close to 20-30%. Correspondingly, the average shortest path, $< l >$, connecting input and output neurons exhibits a minimum value in this range.



Supplementary Figure 5. Distribution of single neuron multiplicity, i.e., number of independent synaptic paths passing through a neuron, for backbones obtained by learning both the AND and XOR rules. Data are collected from 500 configurations of networks with $N = 1000$ neurons and different percentages of inhibitory synapses ($k_d = 3$, $\alpha = 0.001$). The behaviour of the distribution is non-monotonic with p_{in}: Larger values of the multiplicity are observed for 30% inhibitory synapses, suggesting that the backbone is organized in a more intricate structure of interconnected neurons for this fraction of inhibitory synapses.