Context, correlation and decorrelation with randomly connected neurons

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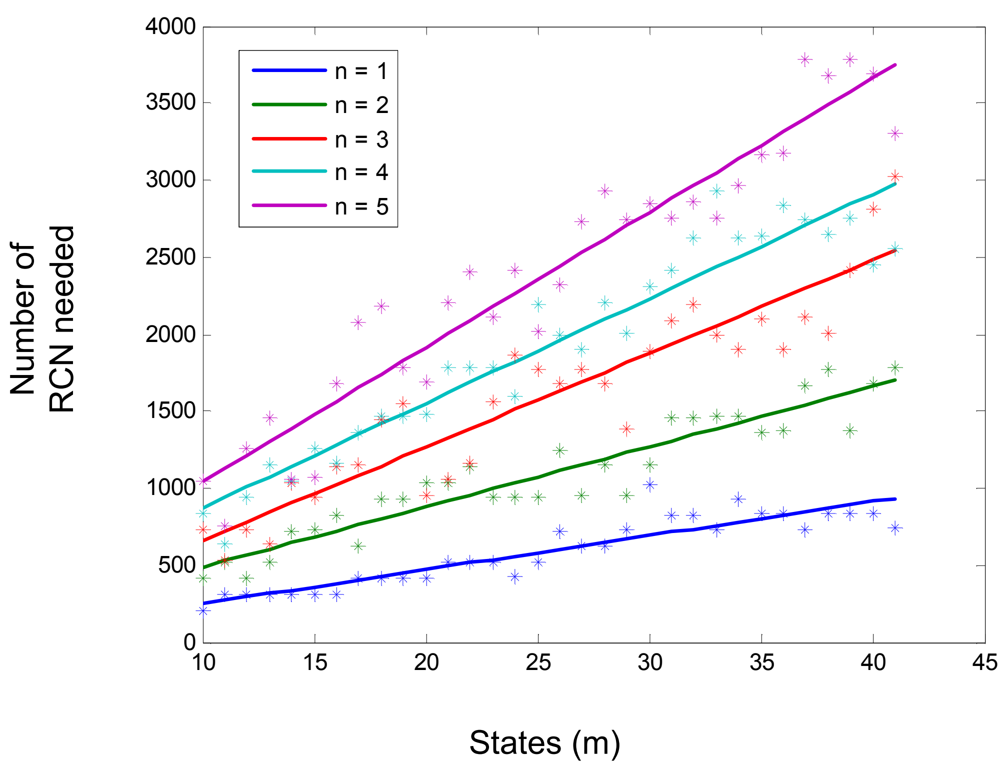
Summary :
Context modulates our responses to external events. We formalize this problem using an event-driven transition scheme between mental states. Each state represents a disposition to behavior, with events inducing transitions to a state that depends on both the previous state and the specific event. This scheme can be realized by two neural populations representing the mental state (recurrently connected internal neurons) and the external event (external neurons). In order to implement a given scheme, we need to find a set of synaptic connections that induces the desired mapping from combinations of current states and events to the next state. Each internal neuron can be regarded as a Perceptron that classifies the mental state-event combinations. Unfortunately, context dependence often generates strong correlations between the Perceptron input patterns, rendering them not linearly separable, and hence there is no proper set of synaptic weights. These problems can be solved by introducing a third population of neurons that are randomly connected to both populations (Randomly Connected Neurons, RCNs) [1]. These neurons exhibit a form of mixed selectivity to the mental state and the external event that is observed in many cortical areas of primates and rodents [2]. By introducing a novel technique to analyze the Perceptron performance using Singular Value Decomposition, we can estimate analytically the required size of the RCN pool in order to solve a given task with a specific noise level. The calculations reveal a trade-off between preserving the input structure and decorrelating it, where the former allows for noise robustness and the latter solves the linear separability problem. We believe that this trade-off (affected e.g. by the RCN coding level) is relevant to a large class of models based on randomly connected neurons. [1] Rigotti et al. Front. Comput. Neurosci. 2010 [2] Assad et al. Neuron 1998

Additional Information :
The analytical formula for the Perceptron margin κ given m mental states, n external events and N_{RCN} Randomly connected neurons is $\kappa \geq \sqrt{\frac{N_{RCN}}{3mn}}$

This implies that for a fixed margin (able to support a given noise level), the number of RCNs should scale linearly with the complexity of the scheme defined as the product mn. Indeed, our simulations show this behavior



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