Information theoretic pruning of recurrent neural networks for task specific adaptation

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Reservoir computing refers to a class of recurrent neural network models, like Echo State Networks [1] and Liquid State Machines [2], which consist of an input layer, a large reservoir layer with random recurrent connections and a layer of trainable readout units, that is capable of performing nonlinear memory dependent computations. Given a sufficiently large reservoir or liquid computing network, these models possess universal computational powers [2] with the ability to approximate any nonlinear function. In principle, large reservoirs have the benefit of being very versatile in application as they are not specialized to a specific task. However, the downside of big, task independent networks is that they comprise a lot of units with relatively small influence on the readout, along with a high training complexity. By relinquishing the versatility of the network, task specificity can be exploited for much smaller networks can reach the same performance as normal sized random networks [3]. Instead of creating problem specific networks from scratch, which can take a lot of time, this work presents a way of adapting random recurrent networks to a given task by reducing it to the most important subset of units.

This simple, information theoretic based algorithm for network pruning incrementally deletes the unit, which shares the least mutual information with the readout units. Using a rate coded neuron model, the algorithm was tested with different initial network topologies, including poisson random graphs, scale-free networks and small-world networks. The tasks, these networks were adapted to, ranged from purely memory dependent to purely nonlinear problems. Not only could the network size dramatically be reduced without impairing the performance, but also did the performance on nonlinear tasks improve after pruning.

Keywords: Recurrent neural networks, complex networks, network pruning, information theory

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