Self-Organisation in Recurrent Neural Networks using Transfer Entropy

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Reservoir Computing (RC) is a recent paradigm in the field of recurrent neural networks. RC computing approaches have been employed as mathematical models for generic neural microcircuits, to investigate and explain computations in neocortical columns (see e.g. [2]). A key element of reservoir computing approaches is the randomly constructed, fixed hidden layer – typically, only connections to output units are trained. Despite their impressive performance for some tasks, their fixed random connectivity can lead to significant variation in performance [1]. To address this issue, approaches like Intrinsic Plasticity (IP) can help to improve randomly constructed reservoirs [3]. IP is based on the idea to maximise available information at each internal unit in a self-organised way by changing the behaviour of individual units. This is contrast to, for example, Hebbian learning, which strengthens connections between two units if their firing patterns are temporally correlated. Both adaptation of individual units as well as adaptation of connections are phenomena that occur in biological units.

IP learning has been used as an approach to optimise reservoir encoding specific to the input of the network [3]. It is, however, *only* dependent on the input data, and does not take the desired output of the system into account, i.e., it is not guaranteed to lead to optimised performance with respect to the learning task of the network [1]. Ideally, we would like to retain the principle of a self-organised approach to optimise reservoirs, but to guide self-organisation based on the overall learning goal.

We are able to present a method that optimises the information transfer at each individual unit, dependent on properties of the information transfer between input and output of the system. The optimisation is achieved by tuning self-recurrent connections, i.e., the means to achieve this optimisation can be viewed as a compromise between Hebbian and IP learning. Using synthetic data, we show that this reservoir adaptation improves the performance of offline echo state learning, and is also suitable for online learning approaches.

Our approach uses a local adaptation of a units internal state, based on properties of the information transfer between input and desired output of the system. It introduces two extra steps to the learning procedure. In a first step, we determine a transfer entropy history size that maximises information transfer between input and output of the network. In a pre-training step, we adapt local couplings of the reservoir units so that the transfer entropy from the input of each unit to its respective output is optimised for the derived history length. After this pre-training of the reservoir, internal connections are frozen and remain fixed during the normal training procedure.

The approach has shown to improve performance in conjunction with offline echo-state regression, as well as with recursive least squares online learning. In this case, the pre-training and the training of the output units are run at the same time (in an interleaving fashion). Our approach is able to cope with only a small number of internal units, but we can also show that for a larger number of units our adaptation leads to an even larger improvement compared to echo state learning without adaptation.

[1] Joschka Boedecker, Oliver Obst, Norbert Michael Mayer, and Minoru Asada. Initialization and self-organized optimization of recurrent neural network connectivity. *HFSP Journal*, 3(5):340–349, October 2009.

[2] Wolfgang Maass, Thomas Natschläger, and Henry Markram. Real-time computing without stable states: A new framework for neural computation based on perturbations. *Neural Computation*, 14(11):2531–2560, 2002.

[3] Jochen J. Steil. Online reservoir adaptation by intrinsic plasticity for backpropagation-decorrelation and echo state learning. *Neural Networks*, 20(3):353–364, April 2007.

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