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Título: Atractor Neural Network: Code, Information and Topology

Abstract:
In the late years there was a huge increase in applications from heuristic methods to big data problems. For instance, machine learning has been used to find near-optimal solutions for computationally expensive in both time and memory, such as DNA sequencing, smart-cities or stock-market forecasting. Most of these algorithms are based on non-lineal regression, with adaptive coupling weights between layers of units, which can store, associate, classify, retrieval or cluster sets of input patterns. However, these models, lets call neural networks, even when they show a complex mixing of long and short term memory, temporal or spatial patterns, backward or forward learning... have a few common characteristics: they use to handle only bi-lineal weights, and each layer is fully-connected, which eventually works well for binary-like unstructured patterns. In this work, we will present two models we introduced some years ago which improve those features, and have recently been applied to real problems. The first is a biquadratic network with squared weights, which maximizes the likelihood entropy for ternary patterns, where there is lack of information about the pieces of the data, or they are too noisy. We show the advantage of using the biquadratic model to enhance the capacity of pattern retrieval in an attractor NN. Next, we describe a metric NN, for which the topology uses either modules or small-world connectivity. Hence one expects the information to spread far and faster than neighbor-connected NN, without being trapped in spurious metastable memories, but save much wire length compared to full-connected NN. We show how such topology can be used to store and recognize spatially correlated patterns.