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Merge SOM for temporal data

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Abstract

The recent merging self-organizing map (MSOM) for unsupervised sequence processing constitutes a fast, intuitive, and powerful unsupervised learning model. In this paper, we investigate its theoretical and practical properties. Particular focus is put on the context established by the self-organizing MSOM, and theoretic results on the representation capabilities and the MSOM training dynamic are presented. For practical studies, the context model is combined with the neural gas vector quantizer to obtain merging neural gas (MNG) for temporal data. The suitability of MNG is demonstrated by experiments with artificial and real-world sequences with one- and multi-dimensional inputs from discrete and continuous domains.

Keywords: Self-organizing map; Temporal Kohonen map; Sequence processing; Recurrent models; Neural gas; Fractal encoding; Finite automata; Speaker identification; DNA splice site detection

1. Introduction

The design of recursive data models is a challenging task for dealing with structured data. Sequences, as a special case, are given by series of temporally or spatially connected observations—DNA chains and articulatory time series are two

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interesting examples of sequential data. Sequential data play a major role in human processing of biological signals since virtually all visual, auditory, or sensorimotor data are given as sequences of time-varying stimuli. Thus, biologically plausible and powerful neural sequence processing models are interesting from a practical as well as from a cognitive point of view.

Unsupervised self-organization is a particularly suitable paradigm for biological learning because it does not rely on explicit teacher information and as it uses intuitive primitives like neural competition and cooperation. Kohonen's self-organizing map (SOM) is a well-known method for projecting vectors of a fixed, usually high dimension onto a low-dimensional grid, this way enabling analysis and visualization [11]. In contrast to the SOM, the neural gas (NG) algorithm yields representations based on prototypes in the data space, which cooperate in a data-driven topology and yield small quantization errors [13]. However, in their original formulations, SOM and NG have been proposed for processing real-valued vectors, not for sequences.

Given sequential data, vector representations usually exist or can be found for single sequence entries. For vector quantizer models, such as the mentioned SOM and NG, temporal or spatial contexts within data series are often realized by means of data windows. These windows are constructed as serialized concatenations of a fixed number of entries from the input stream; problems related to this are a loss of information, the curse of dimensionality, and usually inappropriate metrics. The last issue, inappropriateness, can be tackled only partially by using adaptive metrics [17,19].

Recently, increasing interest can be observed in unsupervised recurrent self-organizing networks for straight sequence processing. Prominent methods are the temporal Kohonen map (TKM), the recurrent self-organizing map (RSOM), recursive SOM (RecSOM), and SOM for structured data (SOMSD) [1,7,24,26]. These are unsupervised neural sequence processors with recurrent connections for recursive element comparisons. Thereby, similarity structures of entire sequences emerge as result of recursive operations. TKM and RSOM are based on biologically plausible leaky integration of activations, and they can be used to explain biological phenomena such as the development of direction selectivity in the visual cortex [4]. However, these two models use only a local form of recurrence. RecSOM and SOMSD use a richer recurrence as demonstrated in several experiments [7,26].

First experimental comparisons of the methods and steps towards an investigation of their theoretical properties have been presented recently in the articles [8,9]. It turns out that all models obey the same recurrent winner dynamic, but they differ in the notion of context; internally, they store sequences in different ways. This has consequences on their efficiency, their representation capabilities, the induced metrics, and the possibility to combine their contexts with different lattice structure. The focus of this work is an investigation of the recent merge SOM (MSOM) approach [20]. MSOM is based upon a very effective context model which can be combined with arbitrary lattice structures: the temporal context of MSOM combines the currently presented pattern with the sequence history in an intuitive way by referring to a merged form of the winner neuron's properties.