Optimal Neural Network Feature Selection for Forecasting of Spatial-Temporal Series

Eurico Covas, others, and many,

***Abstract*—We show empirical evidence on how to construct the optimal feature selection or architecture for the input layer on a neural network used for forecasting of spatial-temporal series. The approach is based on results from dynamical systems, namely the non-linear embedding theorems. We demonstrate it for a two dimensonal signal with one spatial dimension and one time dimension, and show that the optimal input layer seems to consist of a two dimensional grid, with spatial/temporal lags determined by the minimum of the mutual information of the spatial/temporal signal subsets and the number of points taken in space/time decided by the embedding dimensional of signal. We support our evidence by running a Monte Carlo simulation of several combinations of input layer architecture and showing that the one decided by the non-linear embedding theorems seems to be optimal or close of optimal.**

***Index Terms*—IEEE, IEEEtran, journal, LaTeX, paper.**

I. Introduction

IN this paper we show empirical evidence for an optimal architecture of the input layer of a neural network which tries to forecast or predict a spatial temporal signal. Here we show the empiral evidence for two particular cases of two dimensional data series s_m^n (one spatial, one temporal dimension). By two dimensional data series we mean a scalar field which can be defined by a $N \times M$ matrix with components $s_m^n \in \mathbb{R}$.

A. Neural networks for time-series forecasting

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B. Neural networks for spatial temporal forecasting

There has been several attemps to forecast spatial-temporal data series in the literature (add references). The references above confine themselves to articles that attempt to forecast the actual full scalar field s_m^n, as opposed to the ongoing research on pattern recognition in moving images (2D and 3D), which attempt to pick particular features in images (e.g. car, pedestrian, bicycle, person) and to forecast where those features will be in subsequent images within the particular moving sequence.

E. Covas is with the CITEUC, Geophysical and Astronomical Observatory, University of Coimbra, 3040-004, Coimbra, Portugal, and Queen Mary University London, 10 Godward Square, Mile End Rd, London E1 4FZ, e-mail: (eurico.covas@mail.com)

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C. Sunspot and solar data series forecasting using neural networks

Neural networks, among other forecasting methods (add references) has been used extensively to try to predict sunspots and related data series. Mostly this has been done in time only (add references). There are a few examples (add references) of actual spatial temporal forecasts using neural networks (see mine and the one on MDI/HDI data).

D. Input layer architecture for neural networks for spatial temporal forecasting

All of the references above on neural network forecasting of spatial temporal data series either use a simple delay based architecture for the input layer, or use a time delay based on the first minima of the *mutual information* as proposed in [1]–[3]) and/or use the number of points dictated by the embedding theorems by [4], [5], [6] and [7] using the method of *method of false nearest neighbours* detection suggested by [8] and reported in detail in [2], [9]–[11].

However, as far as we are aware, all the references to using the embedding theorems and the related mutual information method and the false nearest neighbours method seems to be not justified, i.e., the approach is explained but not proven either theoretically or empirically.

Here we show two cases, one based on the articles of one of us on sunspot forecasting ([12]–[14]) and one based on the Kuramoto-Sivashinsky (KS) equation (add references and add parlitz paper here)

Several authors [15]–[66] have already attempted to use neural networks to forecast aspects of the sunspot cycle, although none in both space and time, having restricted themselves to using these neural networks to forecast mostly either the sunspot number or the sunspot areas as a function of time.

Takens established the theoretical background [5] in the Takens embedding theorem. Further developments established a series of theorems by [4], [5], [6] and [7].

Some authors discuss the use of either mutual information and/or embedding dimension as a constraint on the input layer, i.e. the feature selection. [24], [27], [30], [55], [57], [63], [66]–[81] used the mutual information and/or the false nearest neighbours' methods to estimate the suitable embedding parameters.

[21], [22], [27], [57], [63], [66], [68] attempted to forecast the solar sunspot number using neural networks and they used the embedding dimension of the sunspot time series as way to define the architecture of the input layer.

[82] generalize the mutual information approach to higher dimensions but do not connect it to the problem of the neural network input layer architecture optimization.

There are also papers [83] that try to use neural networks to determine the optimal embedding and time delay for the purposes of local reconstruction of states with a view to forecast.

There are also papers [84] that use Support Vector Machines (SVMs) to forecast in space and time and use time delays and embedding approachs to define the states vectors.

In fact Parlitz and Merkwirth [85] in the ESANN 2000 meeting proceddings paper mentioned that local reconstruction of states "…may also serve as a starting point for deriving local mathematical models in terms of polynomials, radial basis functions or neural networks.". Here we attempt to show empirical evidence that this is not just a starting point, but the optimal neural network input architecture.

Eurico Covas
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E. Neural Network architecture

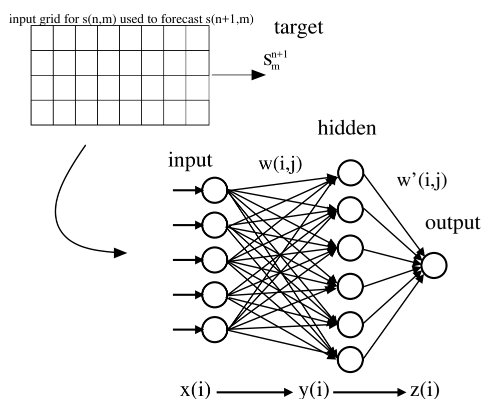

Fig. 1. Overall architecture of the neural network.

1) Monte Carlo results: Subsubsection text here.

II. Conclusion

We have shown empiral evidence for the existence of an optimal architecture of the input layer of neural networks used for forecasting spatial-temporal series.

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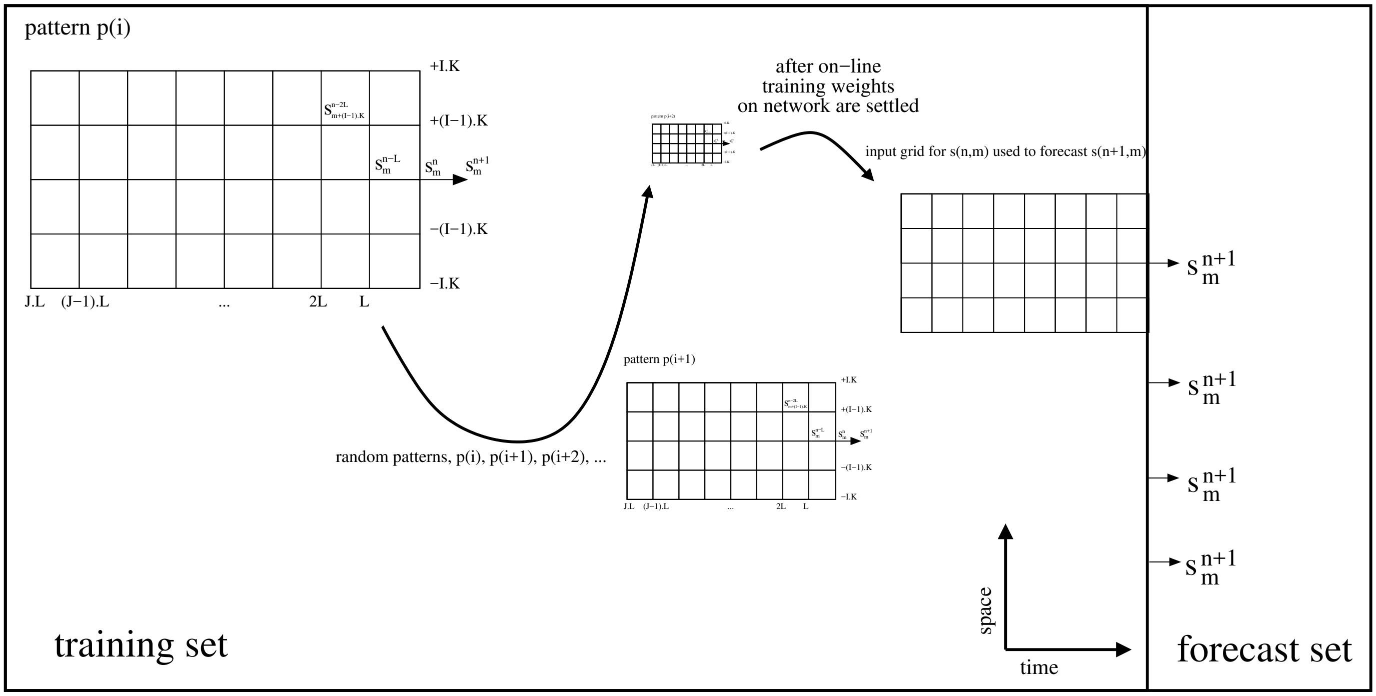

Fig. 2. Neural network architecture showing the feature selection grid.

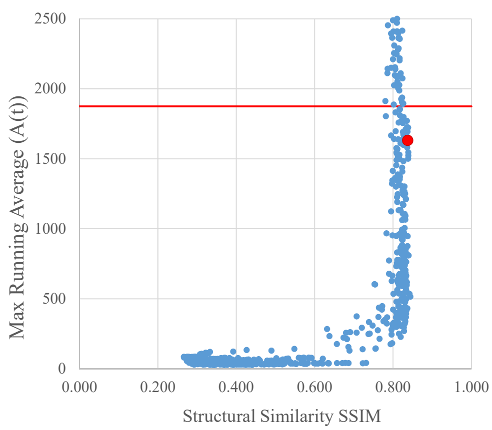

Fig. 3. Monte Carlo simulation of different architectures of the input layer for the neural network forecast. It shows the average of the sunspot area over the next cycle against the structural similarity (SSIM). The perfect architecture would be the one with SSIM = 1 and the 24-month running average over the cycle being the same (red lines).

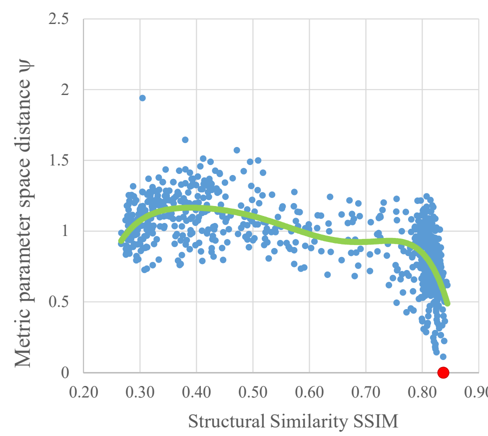

Fig. 4. Monte Carlo simulation of different architectures of the input layer for the neural network forecast. It shows the structural similarity (SSIM) against how far (in an Euclidean space metric) the particular parameters of a particular run were from the supposely optimal architecture parameters (red dot). The green line (trendline) seems to show that as the parameters of a randomly choosen architecture get close to the supposely optimal architecture ones, the SSIM converges to what seems to be the best possible forecast value given the limited (and noisy) dataset.

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