Generation of time response of linear and nonlinear dynamic systems using autoencoders

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Abstract

In this work, a deep autoencoder is used to generate the time response of linear and nonlinear dynamic systems. First, the encoder part of the autoencoder is used to perform a compact representation of the time response of dynamic systems. Second, the decoder part of the autoencoder is used to reconstruct or generate the time response of dynamic systems from the latent space. Experiments are performed to determine the capability of the architecture and the training algorithm proposed for dimensionality reduction, reconstruction, and generation. Finally, the architecture is validated with some examples of linear and nonlinear systems.

1 Research problem and motivation

Autoencoders are feedforward neural networks that use unsupervised learning with the objective of generating new data by first compressing the input into a space of latent variables and then reconstructing the output based on the information acquired. In this way, it is possible to generate new data from the variation of its latent space. These, facilitates the classification, communication, and storage of high-dimensional data[1]. In this work, the main motivation is reconstructing or generating data of the time response of the linear systems from the latent space.
There are dynamic systems whose time response requires many samples, which means that a large enough memory space is necessary if this data is to be stored for later analysis or study, which increases the computational cost. Due to this, a reduction of dimension is important in this case, and a subsequent reconstruction is necessary[4]. Furthermore, a compact representation allows us to eliminate some redundant dimensions of high-dimensional observations and reduce it to low-dimensional characteristics without significant loss of information.

Artificial neural networks are widely applied to different tasks with dynamic systems. Some of the most common are system identification and control. In the past, a multilayer perceptron and recurrent networks have achieved good results in many system identification tasks of linear and nonlinear systems [3].In more recent years and nowadays, other results have been evidenced in the identification of systems where newer architectures have been applied, such as convolutional networks[2] or LSTM networks[5].However, today there are few works where the use of autoencoders and their property of dimensionality reduction applied to dynamic systems is evidenced. Also, neither there are not papers where the reconstruction capability had been studied.

Autoencoders, as a powerful tool for the reduction of dimensionality, have been applied intensively in the reconstruction of images, recovery of missing data and classification problems. But its application in dynamic systems has been little explored. Also, the interpretability of latent space variables is still a challenge, which is why this work is expected in the future allows to relate these variables to the characteristic parameters of a dynamic system, such as the system's tao (first-order systems) or zita (second-order systems), or even with classic identification models such as ARX.

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2 Technical contribution

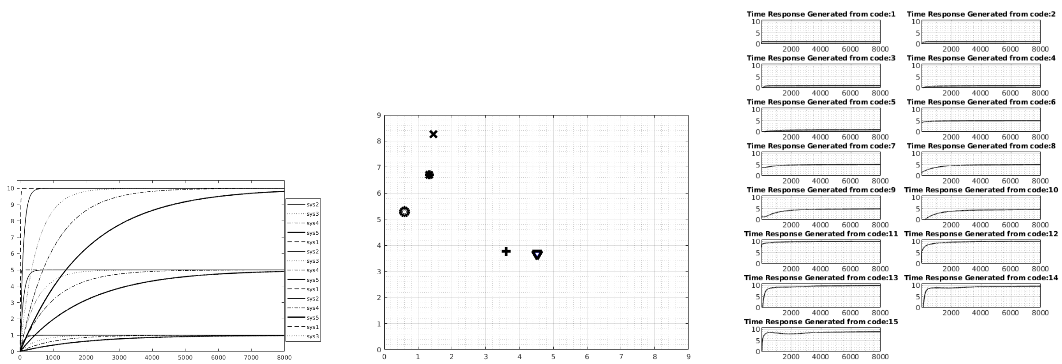
2.1 Dimension of the latent space and compact representation

In order to use AEs to system representation, we use the following approach based on an ARX model for first-order systems with [1, 1, 1] regressor vector

$$y(k) = -a_1 y(k-1) + b_1 u(k-1) \tag{1}$$

Thus, based on the previous approach, we propose a deep autoencoder composed by one input layer (shape=(None, Number of samples)) and six dense layers with 200, 100, 2, 100, 200 neurons each one respectively.The two neurons in the most hidden layer (latent space) is in order to find a compact representation composed of two parameters.

2.2 Results

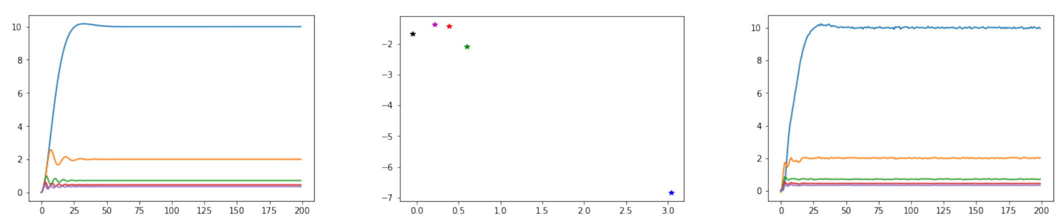


(a) The output of the five first-order systems

(b) Encoder results for linear systems

(c) Time Response Generation From (b)

Figure 1: Results for linear systems



(a) The output of nonllinear system

(b) Encoder results for nonlinear systems

(c) Time Response Generation From (b)

Figure 2: Results for nonlinear systems

In this work, the generation of time responses of linear and nonlinear dynamic systems using autoencoders was demonstrated. First, we got a compact representation from the output data of different systems by using the encoder part. And then, we generated time responses by using the decoder part and from codes in latent space. The interpretability of latent variables remains a challenge. So in future work, this problem will be addressed, in addition to applying other types of structures such as Denoising Autoencoders (DAEs) for systems affected by noise. Finally, this approach is also expected to be extended to perform system identification of linear and non-linear systems.

References

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